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Design Knowledge for Sensitive Social Media Recommender Systems

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Abstract
Recommender systems are among social media sites' most critical components in attracting and retaining users. However, they entail challenges, for example, by inducing social comparison, which harms social media users' well-being. This study developed design knowledge for sensitive social media recommender systems that help to foster users' well-being. It followed an incremental and iterative design science research approach, evaluating sensitive social media recommender systems through a systematic literature review, two qualitative interview series with experts and users, a scientific focus group, and an online survey based on the Kano customer satisfaction model. The study outcomes include a conceptual framework, meta-requirements, design principles, and design features. This work enhances the understanding of making current social media recommender systems more sensitive towards users, enriches the research on digital responsibility, and is one of the first to demonstrate the feasibility of Kano analysis as an evaluation tool in design science research.

Keywords Recommender systems · Well-being · Social media · Design science research · Kano analysis

1 Introduction

Social media sites rely on recommender systems to suggest contacts, products, events, and other content to their users. Recommender systems are software agents (Baird & Maruping, 2021) that detect users' interests and preferences and make corresponding recommendations (Xiao & Benbasat, 2007). The reach of social media recommender systems is vast. For example, TikTok, whose success builds almost entirely on its recommender system-based "For You" page, had over one billion active users in 2023 (Shewale, 2023). Another example is YouTube: The video platform's recommender systems account for over 70 per cent of watch time (Solsman, 2018).

Despite playing a significant role in social media's success and being indispensable, the extensive impact of social media recommender systems implies challenges. Research indicates that commercial recommender systems may prioritise providers' over users' interests (Jeckmans et al., 2013; Xiao & Benbasat, 2007). In social media, this may adversely affect users' well-being. Social comparison and filter bubbles are two prominent examples of adverse implications caused by social media recommender systems. Social comparison (i.e., comparing oneself to others to evaluate one's social situation) on social media can harm users' well-being, reflected in consequences such as self-appraisal deterioration and depression (Steers et al., 2014). Filter bubbles (i.e., being surrounded on social media exclusively by information that corresponds to one's ideological point of view) risk increasing extremist opinions (Kitchens et al., 2020; Markgraf et al., 2019), which can harm those exposed to such views on social media and contribute to broader detrimental societal effects.

Positioning the user and their needs at the centre of social media recommender system design is vital to counter the abovementioned challenges. Our primary aim is not to propose a social media recommender system dedicated solely to enhancing user well-being; rather, we advocate for the

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development of social media recommender systems that actively consider user well-being alongside their manifold other functionalities. By doing so, we aim to mitigate potential negative effects of social media use, such as social comparison and anxiety.

We focus on social media recommender systems (in contrast to recommender systems in general) because of the extremely high global user number of more than 4.5 billion (We Are Social, 2022). Thus, pursuing this endeavour offers tremendous impact potential in fostering users' health and well-being, as recommender systems can facilitate access to relevant preventive and supportive content that enhances positive mental health outcomes (Jafar et al., 2023). Furthermore, the potential influence of these recommender systems on users is very specific to the context of social media with, for example, social comparison (Mackson et al., 2019) and triggered emotions (Golbeck, 2019) in social media instead of a recommended product leading into a purchase in, for example, e-commerce recommender systems. Hence, we consider developing systematic knowledge on this matter highly relevant and aim to answer the following research question:

How should recommender systems in social media be designed to be sensitive towards their users' needs? This research question leads us to the following design objective.

Design Objective We aim to develop design knowledge for sensitive social media recommender systems (SSMRS) comprising four design artefacts: (1) a conceptual framework that models key functionalities and the stakeholder context, forming a foundation for design decisions, (2) a set of meta-requirements constituting the scope of the SSMRS design knowledge, (3) a set of design principles that abstractly describe SSMRS functionality, and (4) a set of design features as functional design knowledge.

Per our definition, SSMRS are sociotechnical information systems (IS) that aim to enhance social media users' well-being through responsible and individualised recommendations while respecting privacy. Moreover, SSMRS seek approval from key stakeholders, extending beyond just the users. SSMRS offer the opportunity to address the problem of under-prioritising users' needs through more sensitive recommendations. SSMRS, as per the social impact-focused design science research (DSR) guidelines by De Leoz and Petter (2018), are sociotechnical IS comprising three main subcomponents: (1) a social subcomponent centred around the social media user, (2) a technological subcomponent represented by the recommendation engine, and (3) an information subcomponent primarily consisting of user and content data. The design knowledge we developed in this study combines these subcomponents, focusing on applicability and feasibility to enable social media recommender systems to be more sensitive in practice. An earlier paper offers preliminary views of selected aspects of the design knowledge presented here, particularly on the conceptual framework, the meta-requirements, and the design principles (Bonenberger et al., 2022).

From a methodological perspective, we followed the iterative and evaluation-centred DSR process by Sonnenberg & vom Brocke (2012a). The SSMRS design knowledge integrates two scientific modes. The conceptual framework, meta-requirements, and design principles stem from inductive analyses of literature and expert knowledge. The design features are derived deductively from the literature using the design principles as a template. Regarding the evaluation activities, we first integrated knowledge from a systematic literature review and interviews with system design, social media, and psychology experts to evaluate and validate the design objective. We then evaluated the developed SSMRS design knowledge in additional interviews with experts and social media users, a focus group with IS scholars, and an online survey building on the Kano customer satisfaction model (Kano et al., 1984) with 249 social media users.

From a research perspective, this study provides knowledge on how to reduce and turn harm from social media use into benefits by providing operational design knowledge for social media recommender systems, and on which stakeholders play a role in that context. The study contributes to responsible digitalisation (Recker et al., 2022) by combining the digital responsibility principles of functionality, norms and values, data privacy, fairness, and transparency (Trier et al., 2023) in sensitive social media recommendations. Further, it is one of the first studies to demonstrate the feasibility of Kano analysis as a DSR evaluation tool. In practical terms, the study provides a foundation for social media site providers to make their recommender systems more sensitive towards users.

As we do not believe that the primary goal of social media site providers will become increasing their users' well-being and health because of other stakeholders' interests—and, so far, there is no existing social media site with this disclaimed goal— we provide insights on potential features that are sensitive to selectively foster users' well-being and health. Therefore, the SSMRS design knowledge can be used to advance social media site providers' business models by putting their customers' well-being and health more to the front.

2 Theoretical Foundations

2.1 Implications of Social Media Use On Individual Well-Being and Health

Social media can affect individuals' well-being. Individual well-being is a central construct of positive psychology. Scholars have proposed various conceptualisations of well-being, among them hedonic and eudaimonic views (Deci & Ryan, 2008). The hedonic view emphasises happiness, the experience of positive feelings, and the absence of negative feelings (Diener et al., 1999). The eudaimonic view dates back to Aristotle, who believed happiness emerged from engaging in worthwhile endeavours (Ryan & Deci, 2001). While these perspectives are conceptually related, they are also empirically distinct (Keyes et al., 2002). The eudaimonic perspective characterises well-being as more process-like than outcome-based (Deci & Ryan, 2008). Individuals experience well-being, for example, when they have a positive attitude towards themselves, are self-determining and independent, and have aims in their lives (Ryff & Keyes, 1995). Conversely, poor well-being may be reflected, for example, in being isolated and frustrated in interpersonal relationships, having difficulties in managing daily affairs, and feeling bored with life (Ryff & Keyes, 1995). A strong connection exists between well-being and individuals' health. Health encompasses the human body and the mind, and well-being plays a crucial role in preventing and recovering from illness (Ryff & Singer, 1998).

Existing research has investigated the influence of social media use on users' well-being and health. Whether social media use has positive or negative implications depends on how it is used. Active social media use, such as building social connections, can foster well-being (Verduyn et al., 2017), whereas passive use, such as browsing without interaction, may have adverse effects due to mechanisms like social comparison and envy (Verduyn et al., 2017; Wang et al., 2018). However, these patterns are not always consistent. For example, a study on the connection between Instagram use and loneliness discovered that passive use (e.g., only browsing content) might result in well-being benefits, whereas more active use (e.g., broadcasting) may imply adverse outcomes (Yang, 2016).

Social comparison has emerged as one of the most prominent mechanisms influencing well-being in the context of social media use. Facebook use, for example, may negatively impact women's self-assessment and well-being due to social comparison (Fardouly et al., 2015). Another study found that social comparison on Facebook implied adverse mental health outcomes for both men and women (Steers et al., 2014). Similar effects were observed on Instagram, where social comparison was associated with reduced well-being, although the same study also noted well-being benefits for users compared to non-users (Mackson et al., 2019). Laboratory experiments and an experience sampling study on Facebook, Twitter, and Instagram have further demonstrated the negative influence of social comparison on users' well-being (Fan et al., 2019; Wirtz et al., 2021).

In addition to social comparison, social media can impact well-being through exposure to emotionally positive or light-hearted content. For example, seeing animal pictures on one's feed has been found to foster well-being (Golbeck, 2019). A self-report study revealed a predominantly positive connection between adolescents' social media usage and well-being, though additional in-depth interviews pointed to both positive and negative implications (Weinstein, 2018).

Other facets of social media use also play a role. Building both closer and looser social connections through social media can positively impact well-being (Ostic et al., 2021). At the same time, outcomes such as isolation and smartphone addiction are associated with negative well-being implications (Ostic et al., 2021). Furthermore, telepresence as part of the flow experience when using social media can lead to increased depression and anxiety levels in users (Roberts & David, 2023), and using multiple social media sites connects to higher depression and anxiety levels in young adults (Primack et al., 2017).

2.2 Social Media Recommender Systems

One of the most critical elements of today's social media sites is recommender systems. Recommender systems are *"software agents that elicit the interests or preferences of individual users for products, either implicitly or explicitly, and make recommendations accordingly"* (Xiao & Benbasat, 2007, p.137–138). They aim to counter information overload, a problem inherent in our information technology-dominated world (Yousefian Jazi et al., 2021). Initially, two design paradigms for recommender systems are content-based and collaborative filtering. In *content-based* filtering, a recommender system makes recommendations for items similar to ones that users have liked in the past, stored in a user preference profile (Lops et al., 2011). In *collaborative* filtering, a recommender system uses ratings from a collection of users to determine which item a specific user might like but has not yet considered (Elahi et al., 2016). Besides these two initial paradigms, other filtering techniques for recommender systems have evolved. *Utility-based* recommender systems make recommendations by maximising a utility function for each item for the user, for example, in e-commerce applications (Huang, 2011). *Knowledge-based* recommender systems build on domain knowledge to match items with users' needs (Tarus et al., 2018). This domain knowledge can be in the form of predefined rules, for example, which link item properties with user requirements (Felfernig et al., 2015). In this way, one can rule out the recommendation of content such as gambling or alcohol to minors. In practice, *hybrid* recommendation techniques combine the properties of the abovementioned approaches. For example, there exist combinations of content-based, collaborative, and knowledge-based filtering for movie recommendations (Walek & Fojtik, 2020) or collaborative and knowledge-based filtering for recommending points of interest in social media (Noorian Avval & Harounabadi, 2023).

Social media recommendations are versatile. They include texts, photos, videos, contacts, locations, events, and products. However, not every recommendation is relevant for every user at every time or place. Traditional recommender systems only consider two entity types: the user and the items to be recommended, which is insufficient for context-dependent use cases (Adomavicius & Tuzhilin, 2011), such as in social media. *Context-aware* recommender systems can overcome this limitation. They incorporate contextual factors such as time, location, user activities, state of mind, mood, and social context (e.g., the user is alone or in a group) to make recommendations (Adomavicius et al., 2011). Conveniently, much of this information is available to social media sites, which can exploit it to make context-aware recommendations. Examples of context-aware social media recommender systems include systems building on users' affective states (Wu et al., 2017) and dynamic user profiles considering behaviour, activities, and social media contacts (García-Sánchez et al., 2020).

In addition to context awareness, research has also addressed other recommender system characteristics that are particularly relevant for sensitivity towards users. For example, fair recommender systems aim to ensure that users receive equally good recommendations regardless of individual differences such as race or gender (Liu et al., 2022). A second example is explainable recommendations, explaining why items are recommended to improve user satisfaction (Lyu et al., 2022). A third example is the consideration of diversity in recommendations through algorithmic (Gogna & Majumdar, 2017) or editorial approaches (Herm-Stapelberg & Rothlauf, 2020).

Overarchingly, we identified two research streams to inform our research objective of developing SSMRS design knowledge. The first stream covers research on social media implications on users' well-being and health (e.g., Erfani & Abedin, 2018; Weinstein, 2018). It indicates that social media can have both positive and negative implications on well-being and health due to, for example, social comparison or social isolation. The second research stream covers social media recommender systems in general, such as for context-based advertisements (e.g., García-Sánchez et al., 2020), and research on recommender systems taking into account users' emotions as a contextual factor (e.g., Yousefian Jazi et al., 2021), being more transparent (e.g., Lyu et al., 2022), and providing more diverse recommendations (e.g., Herm-Stapelberg & Rothlauf, 2020). This stream provides the foundation our work can build on to design recommender systems in a more sensitive way and address problems included in the first stream.

While, with this, we have behavioural knowledge on social media and well-being, we do not know how social media must be designed to be more sensitive towards their users' well-being and which design characteristics of social media foster positive and decrease negative effects. Thus, with this paper, we set out to close this gap to achieve more sensitive social media recommender systems. Therefore, we combine existing behavioural knowledge on social media use and well-being and design knowledge on recommender systems.

3 Research Process

We followed the DSR paradigm (Hevner et al., 2004), aiming to develop design knowledge for SSMRS in the form of operational design artefacts (Gregor & Hevner, 2013). We adopted the DSR process by Sonnenberg & vom Brocke (2012a), which stands out for its tight and continuous design and integration of evaluation activities. The process leads incrementally to the final design artefacts and allows any number of iterations to achieve the design objective. Examples of its application include reducing information asymmetry between humans and artificial intelligence (Vössing et al., 2022), the design of augmented reality smart glass applications in healthcare (Klinker et al., 2020), and the design of support systems for knowledge workers to get more often into "the flow" at work and, thus, experience higher well-being (Adam et al., 2024). The research process by Sonnenberg & vom Brocke (2012a) comprises four design activities, which we implemented as follows: (1) *Identify problem*—we formulated a problem statement, research gap, and design objective for our research project; (2) *Design*—we developed an initial conceptual framework, initial meta-requirements, and initial design principles for SSMRS as conceptual design artefacts; (3) *Construct*—we complemented the conceptual design with a set of initial design features (i.e., specific ways to implement the design principles in an SSMRS) as a functional design artefact and refined the meta-requirements and design principles; (4) *Use*—we refined the design features towards use in a practical context. Four associated evaluation activities accompany the design activities. *Eval 1* ensures the meaningfulness of the research problem at hand. *Eval 2* demonstrates that the proposed artefact design suits solving the research problem. *Eval 3* demonstrates how the designed artefact interacts with its environment. *Eval 4* shows that an artefact is applicable and valuable in practice. Figure 1 visualises our instantiation of the research process.

Identify Problem and Eval 1 We began our research with the understanding that popular social media sites often lack sensitivity to their users, leading to negative impacts on users' well-being (e.g., Mackson et al., 2019; Wirtz et al., 2021) and overall health (e.g., through depression; Steers et al., 2014). Given their significant influence (e.g., Solsman, 2018), we identified social media recommender systems as

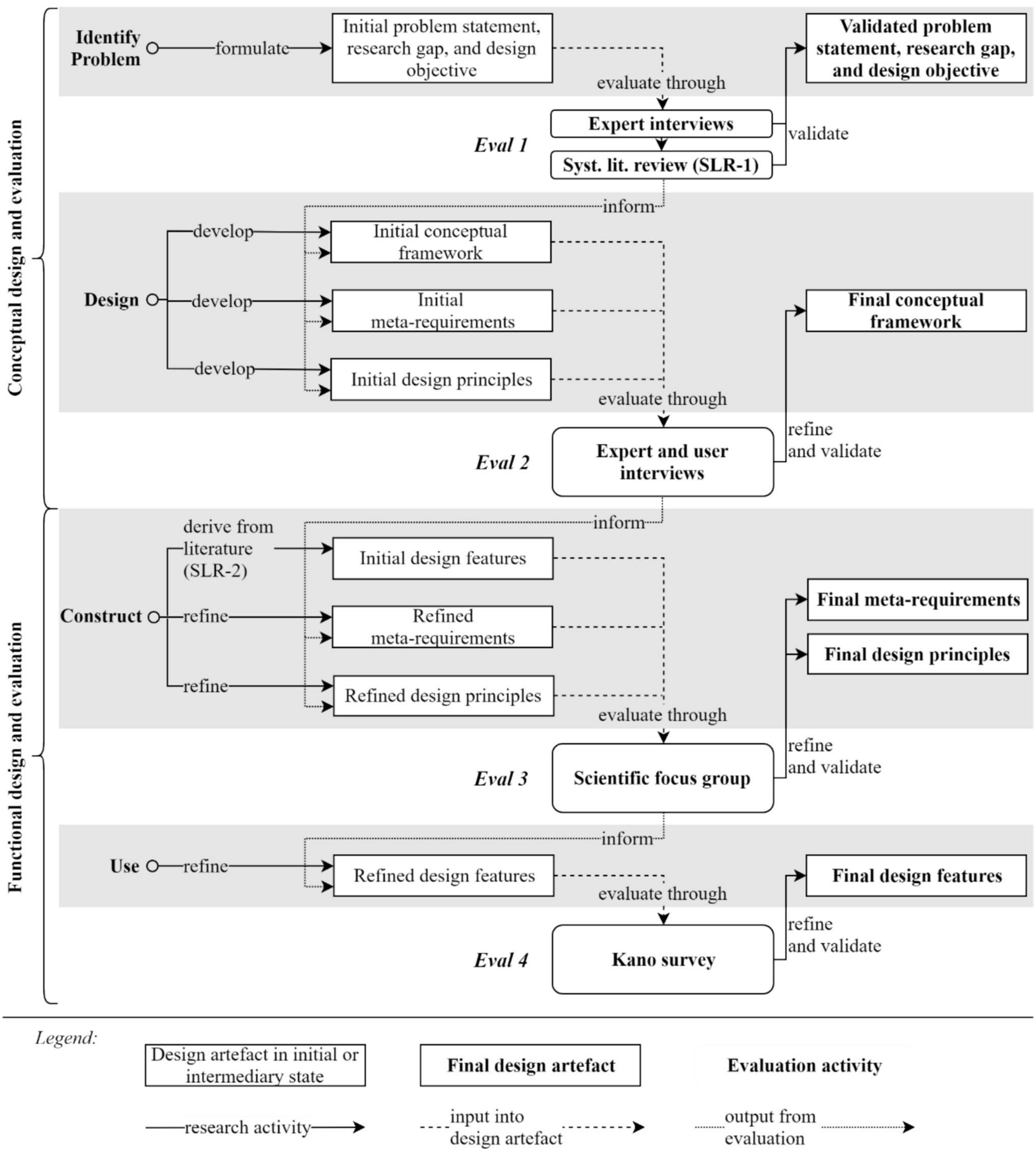

Fig. 1 DSR process following Sonnenberg & vom Brocke (2012a)

a key tool for addressing this issue. Based on this understanding, we formulated our study's problem statement, research gap, and design objective. These three components, referred to as the research outline, served as the input for Eval 1, where they were validated through a qualitative expert interview series, supplemented by a systematic literature review (SLR-1). Accordingly, the output of Eval 1 was validated versions of the problem statement, research gap, and design objective. Additional outputs of Eval 1 included studies addressing related problems in different ways and a rich set of interview data for further analysis beyond validating the research outline.

Design and Eval 2 After validating the research outline, we developed an initial conceptual design for SSMRS, comprising three artefacts: an initial conceptual framework, three initial meta-requirements, and six initial design principles. The conceptual framework models the key functionalities and stakeholder context of SSMRS, providing a foundation for understanding the rationale behind the study's design decisions. The meta-requirements define how to purposefully address the problem space, focusing on making social media recommender systems more sensitive. The design principles offer conceptual guidance for designing SSMRS while allowing for adaptation to specific application contexts. Additionally, the meta-requirements and design principles serve as a foundation for system designers to evaluate their designs using scientific insights.

The initial versions of these artefacts were developed from the insights gained during the Eval 1 interviews, which included exploratory and confirmatory questions, as well as SLR-1. These initial versions of the conceptual framework, meta-requirements, and design principles served as the input for Eval 2. Evaluating these initial artefacts through a second qualitative interview series with experts and social media users led to the validation of the conceptual framework, which received consistent approval, as one part of the output of Eval 2. The second part of the output was actionable feedback on the meta-requirements and design principles.

Construct and Eval 3 We aimed to complement the previously developed design knowledge with design features, a more functional component compared to the design principles. Design features provide functional guidelines (or implementation principles, Gregor & Jones, 2007) that demonstrate how to implement an SSMRS in alignment with the meta-requirements and design principles. System designers can use these features as key references when developing SSMRS for specific contexts and applications. Integrating design features into design knowledge has been demonstrated in DSR, such as designing user interfaces for social media hate speech detection (Meske & Bunde, 2022) and mobile stress assessment systems (Bonenberger et al., 2023). We derived 15 initial design features deductively from the literature using the refined design principles as a template and conducted a second systematic literature review (SLR-2). Additionally, also as part of the construct activity, we refined the meta-requirements and the design principles based on the actionable feedback from Eval 2, with the aim of subjecting them to a second round of evaluation. The 15 initial design features, along with the refined meta-requirements and design principles, served as input into Eval 3. The output from Eval 3, a scientific focus group, included the validation of the meta-requirements and design principles, along with actionable feedback to further refine the initial design features.

The key distinction between the construct phase and the design phase (and their connected evaluation activities Eval 2 and Eval 3) lies in the nature of the artefacts. Artefacts developed in the design phase are purely conceptual and evaluated in a theoretical context, while those created in the construct phase exhibit interactional characteristics within their application context, enabling evaluations to provide initial insights into their utility (Sonnenberg & vom Brocke, 2012a). In our study, these interactional characteristics are reflected in the design features, which we derived from existing studies that examined them in specific application contexts. During the Eval 3 focus group, participants—drawing on their own social media experiences—were able to evaluate these features for their utility.

Use and Eval 4 As part of the use activity, we refined the 15 initial design features based on the Eval 3 focus group results and prepared them for evaluation in a practical context. This refinement resulted in 11 revised design features, each supported by illustrative mobile screen mock-ups and brief descriptions. We selected the Kano survey (Kano et al., 1984) as the evaluation tool, as it is well-suited for assessing product features (Matzler et al., 1996). The 11 refined design features served as input into Eval 4, and the output was the results of the quantitative Kano analysis, which led to the final revision of these features into a set of 11 final design features.

The key difference between the use phase and the construct phase, along with their connected evaluation activities Eval 3 and Eval 4, lies in context. The use phase demonstrates artefact applicability and usefulness in a practical context, while the construct phase requires the artefact to exhibit characteristics suitable for such a context without full integration (Sonnenberg & vom Brocke, 2012a). Since integrating experimental features into a live social media platform is nearly impossible for an independent scientific project, we simulated this context in our study by creating PhotoNetwork, a social media site modelled after platforms like Instagram, using detailed, realistic screen mock-ups for survey participants to engage with.

4 Conceptual Design and Evaluation

This section presents the methodological procedure used to conduct the design activities *Identify problem* and *Design* and the evaluation activities Eval 1 and Eval 2. It further presents the final conceptual artefacts: the conceptual framework, meta-requirements, and design principles. Please note that we refined the meta-requirements and design principles partly using feedback from the focus group reported in Section 5.

4.1 Conceptual Design Methodology

We developed the conceptual design from two knowledge sources: the Eval 1 interview data and the SLR-1 results. Although Eval 1 primarily intended to evaluate and validate our research outline, we included exploratory questions in the interviews to help us develop conceptual knowledge, and we also paid attention to such knowledge when analysing the results of SLR-1.

4.1.1 Expert Interviews (Eval 1)

As part of Eval 1, we conducted a qualitative interview series to validate our research outline—comprising the problem statement, research gap, and design objective as input. A complementary goal was to explore potential design characteristics for SSMRS, laying the groundwork for the study's conceptual design phase. The interviews included participation from three system design experts, two psychologists, and one social media expert, ensuring interdisciplinary perspectives (IS, psychology, sociology). All interviews were conducted in German, one-on-one via video conferencing software, recorded, and transcribed for analysis.

The interviews were semi-structured and guided by an 18-question interview guide. In designing the interview guide, we referred to a DSR study on flow support systems (Adam et al., 2024), which utilised the DSR process by Sonnenberg & vom Brocke (2012a) in a similar way. Additionally, we conformed to an applicability check according to Rosemann & Vessey, (2008), ensuring practical relevance in our research.

The evaluation questions targeted six criteria proposed by Sonnenberg & vom Brocke (2012a): importance, accessibility, suitability, novelty, feasibility, and applicability. Further, we included exploratory questions to gather expert insights for developing the meta-requirements and design principles.

After transcribing the interviews, we coded the results deductively along the problem statement, research gap, and design objective, establishing these as the initial themes. Validation of the research outline involved identifying clear conceptual objections to the problem statement, research gap, and design objective as presented. We found no such objections, and the research outline was validated with minor rephrasing suggestions. Details on the Eval 1 interview guide, interviewees, and illustrative statements are provided in Supplementary Material B.

4.1.2 Structured Literature Review (Eval 1)

We carried out SLR-1 based on the criteria by Webster and Watson (2002) for two reasons. First, it supported the validation of our research outline. While the expert interviews confirmed the practical relevance of the research problem, SLR-1 helped identify existing research related to the design objective and confirm that no SSMRS have been designed according to the approach in this study. Literature reviews have been explicitly endorsed for this purpose in DSR (Sonnenberg & vom Brocke, 2012a; Sonnenberg & vom Brocke, 2012b). Second, SLR-1 provided valuable insights for the conceptual artefact design in the next phase of the project. Based on these goals, we searched the databases Web of Science, IEEE xPlore, ACM Digital Library, APA PsycInfo (all title search), and AIS eLibrary (title plus abstract search because the title search yielded hardly any hits) with the search query *("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*"))*. We selected the keywords "empath*" and "emot*" to capture empathy and emotional awareness, both essential for fostering well-being and addressing users' psychological and emotional health in the social media context, aligning with our concept of SSMRS.[1] The keyword "well-being" was not included because, at this stage of the research process, the primary outcome of interest was the systems' empathetic response to users, whereas well-being was considered a higher-level, indirect user outcome rather than a direct functional property of the system.

[1] At this stage of the research process, we used the designation *empathetic recommender systems in social media*. In the later course of the project, we changed this to *SSMRS*, as we found that "sensitive" better reflects the desired system characteristics from an IS perspective, in contrast to the interpersonal connotations of "empathy.".

The keyword "health" was excluded to avoid skewing the results toward medically focused studies, which are less relevant to the IS perspective of this research.

The search yielded 785 hits, with four duplicates removed, leaving 781 studies for analysis. We applied three inclusion criteria: (1) the study addresses recommender systems or similar systems leveraging users' states of mind for recommendations, (2) it explicitly examines recommender systems in the social media context, and (3) it explores system design related to empathy, well-being, or emotions. We excluded studies with a predominantly medical perspective, as our research focuses on IS aspects.

Abstract screening based on these criteria reduced the set to 71 potentially relevant articles (details in Supplementary Material A), which we then reviewed in detail, further applying the criteria to their content. This process yielded seven articles. To supplement the search, we conducted forward searches (identifying relevant articles citing the selected works), backward searches (examining references in the selected works), and complementary searches using related keywords. The complementary searches confirmed the suitability of our original search query by verifying that it effectively captured the key terms, while also identifying a few additional relevant studies. Forward, backward, and complementary searches identified 18 more articles, resulting in a final set of 25 articles (details in Supplementary Material A).

The large number of hits analysed, compared to the small number of relevant articles identified, suggests that existing studies in the IS discipline and related fields have not addressed the research problem as this study intends. Specifically, the keyword combination of recommender systems and social media yielded few results related to the design objective, further validating the research outline, as previously supported by the positive outcomes from the Eval 1 expert interviews. We present the results of Eval 1 in Section 4.2.

4.1.3 Expert and User Interviews (Eval 2)

The outputs of Eval 1 extended beyond the validation of the problem statement, research gap, and design objective. They included a list of studies addressing related problems in diverse ways (as identified in SLR-1) and a rich set of interview data, which provided material for further analysis beyond validating the research outline. These outputs served as key inputs for the subsequent design activity, enabling the development of three conceptual design artefacts: an initial conceptual framework, a set of initial meta-requirements, and a set of initial design principles.

The development process drew on a qualitative thematic analysis (Nowell et al., 2017) of the interview data and literature, which resulted in three final themes. The *key stakeholder* theme was identified inductively through insights from the interview data, reflecting the need to consider stakeholders beyond the social media user in SSMRS design. In contrast, the *high-level system characteristics* and *design characteristics* themes were set deductively, guided by the overall research process and design objective.

We first incorporated the identified stakeholders into the initial conceptual framework. Next, we examined the interview data and studies from SLR-1 for common high-level system characteristics aligned with the design objective. These characteristics were clustered by the research team, resulting in three initial meta-requirements, with no predetermined number. Finally, we applied the same process to identify more specific design characteristics, leading to six initial design principles. We present the conceptual framework in Section 4.3, the final meta-requirements in Section 4.4 and the final design principles in Section 4.5.

In Eval 2, we evaluated the initial versions of the conceptual framework, meta-requirements and design principles through a second interview series. Participants included one system design expert, a communication psychologist, one social media expert, and three social media users. We selected the experts to provide diverse perspectives on the research, as in Eval 1, while social media users were included to enrich the evaluation with a user perspective. The social media users, who were IS researchers familiar with DSR, were specifically asked to adopt a user perspective during the interviews. The semi-structured Eval 2 interviews were conducted one-on-one in German via video conferencing software, recorded, and transcribed for analysis. Like in Eval 1, the structure of the interview guide was inspired by a DSR study on flow support systems (Adam et al., 2024), which followed the DSR process by Sonnenberg & vom Brocke (2012a) in a manner similar to this study. The interview guide included 13 questions focused on the initial conceptual framework, meta-requirements, and design principles. The Eval 2 interviews addressed evaluation criteria proposed by Sonnenberg & vom Brocke (2012a): clarity and accessibility, suitability, completeness, level of detail, applicability, and feasibility. We coded the interview results deductively using the initial design artefacts as themes. Building on the interview data—the output of Eval 2—we validated the conceptual framework with minor adjustments and obtained actionable feedback for refining the initial meta-requirements and design principles. Details on the Eval 2 interviewees and the interview guide are provided in Supplementary Material C.

Since Eval 2 provided actionable feedback on the initial meta-requirements and design principles, we planned a second round of evaluation for these artefacts. The refinement based on the feedback provided and its evaluation were integrated into the subsequent construct activity and Eval 3, where a focus group served as the additional qualitative evaluation method. Consequently, we refined the initial meta-requirements and design principles based on the Eval 2 feedback in the construct activity and used them as input into Eval 3. Details on this refinement and second evaluation are discussed in Section 5.1 and Section 5.1.1. To maintain a clear structure in this paper and present the conceptual design artefacts alongside their development methodology, we provide the final versions of the meta-requirements and design principles in Sectio 4.4 and Section 4.5.

4.2 Validated Research Outline

The primary outcome of Eval 1 is the validation of this study's research outline. This outline comprises three key elements: a problem statement emphasising the practical significance of the study's subject, a research gap underscoring the need to address the problem based on the state of existing research, and a design objective specifying the artefacts that can bridge the research gap and address the identified problem. Table 1 presents these validated elements of the research outline.

In addition to validating the research outline, Eval 1 provided further insights related to existing systems and stakeholders relevant to the research context. While no studies were found that explicitly designed SSMRS according to, or closely aligned with, that stated design objective, even with the broad scope of SLR-1, the structured literature review revealed two types of systems with related goals.

First, some systems aim to enhance user well-being through specific technological adaptations, such as collaborative filtering in social media recommender systems (Golbeck, 2020a). However, this approach focuses narrowly on a single technology rather than the broader scope envisioned for SSMRS. Other examples include introducing empathy in social agents (Paiva, 2011), which promotes sensitivity in IS at a more abstract level, not limited to recommender systems or the social media context, and providing empathetic feedback in virtual assistants (Prendinger & Ishizuka, 2007), showcasing another use case of sensitive system behaviour outside both the recommender systems and social media domains.

Second, some studies focus on capturing users' states of mind to generate recommendations. Examples include sentiment analysis of social media texts (Brady et al., 2021) and tracking changes in psychological states through social media language (Eichstaedt & Weidmann, 2020). While these approaches are valuable for informing SSMRS design, they focus only on capturing users' states, whereas the envisioned SSMRS design is more comprehensive. Similarly, emotion-aware music recommender systems (Ayata et al., 2018; Polignano et al., 2021) assess users' affective states but are limited in scope, as they neither address the social media context nor encompass the broader objectives of SSMRS.

Additionally, analysis of the Eval 1 interview data revealed key stakeholders relevant to the research context, as highlighted by the experts interviewed. While the study has always focused on social media users, the expert feedback emphasised the importance of noticing other stakeholders, particularly regarding system acceptance. To address this feedback, the conceptual framework in Section 4.3 includes these stakeholders, ensuring that design knowledge for SSMRS accounts for their influence, even with the primary focus on user needs.

4.3 Conceptual Framework

The conceptual framework in Fig. 2 illustrates the research context, centred around the social media user as the primary stakeholder (i.e., the social subcomponent) and a sensitive recommender engine within a social media site as the technological subcomponent. The recommender engine captures the user's state of mind to generate contextually appropriate, sensitive context recommendations aimed at enhancing key user needs such as well-being, health, and data privacy (highlighted by the Eval 2 interviewees).

The framework also identifies additional stakeholders situated at the boundaries of the research context. These

Table 1 Overview of the validated research outline

Validated problem statement	Social media sites use recommender systems to suggest contacts, products, events, and other content, leveraging their extensive reach from massive user bases (e.g., We are Social, 2022). Studies show that commercial recommender systems may prioritise providers' interests over users' (Jeckmans et al., 2013; Xiao & Benbasat, 2007). Since certain recommendations can harm users' well-being (Golbeck, 2019), the absence of sensitive social media recommendations emerges as a significant concern
Validated research gap	Although extensive research examines the positive and negative impacts of social media on users' well-being and health (e.g., Erfani & Abedin, 2018; Weinstein, 2018), there is still limited understanding of how to design social media platforms to be more sensitive to users' well-being and which design features can enhance positive effects while mitigating negative ones
Validated design objective	We aim to develop design knowledge for sensitive social media recommender systems (SSMRS) comprising four design artefacts: (1) a conceptual framework that models key functionalities and the stakeholder context, forming a foundation for design decisions, (2) a set of meta-requirements constituting the scope of the SSMRS design knowledge, (3) a set of design principles that abstractly describe SSMRS functionality, and (4) a set of design features as functional design knowledge

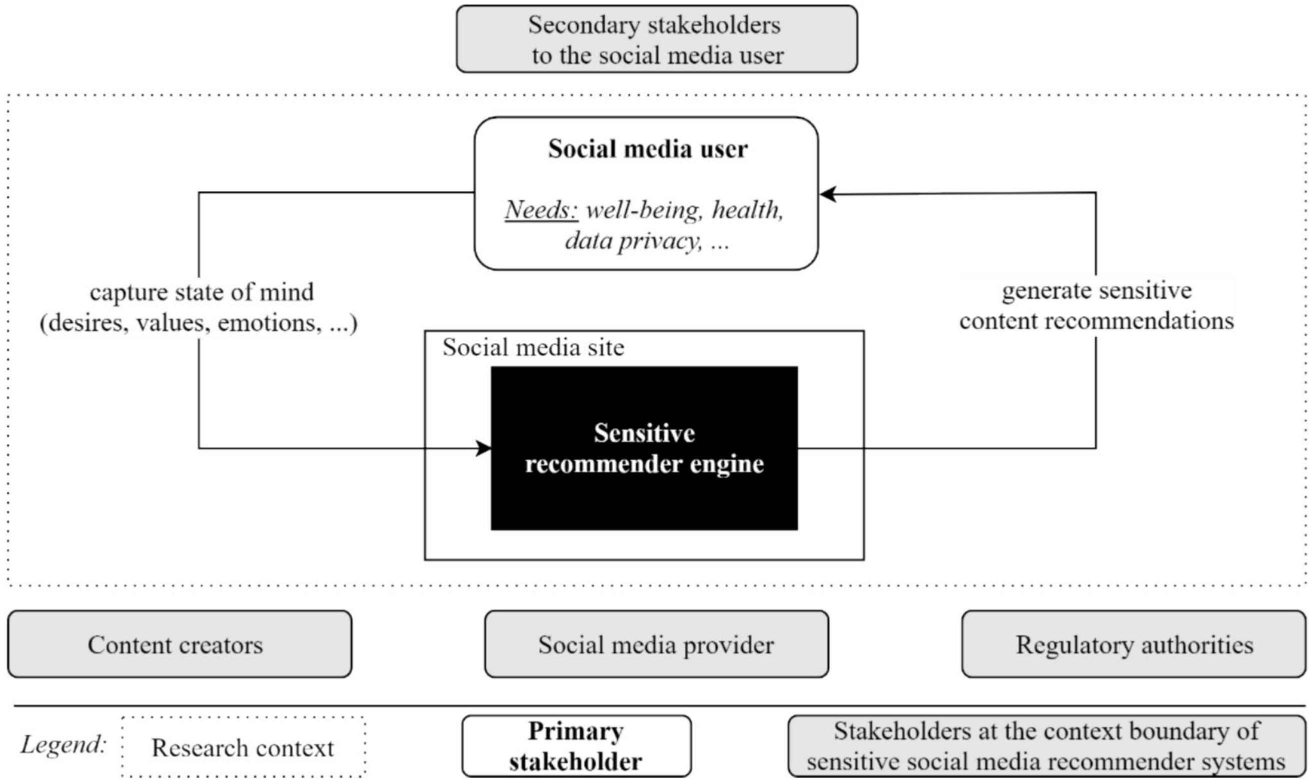

Fig. 2 The conceptual framework for sensitive social media recommender systems

include the site provider, content creators (e.g., organisations, advertisers, or influencers), regulatory authorities, and secondary stakeholders such as friends, family members, or therapists, who support the user in practicing healthy social media habits. While the site provider's and content creators' needs are business-oriented, the users' needs—and by extension, those of secondary stakeholders—are well-being focused. Regulatory authorities are solely concerned with ensuring legal compliance.

The interactions between the social media user and the recommender engine are detailed through the meta-requirements and design principles below. As this study prioritises user needs, the interactions of other stakeholders with the social media site and user are discussed only briefly.

4.4 Final Meta-requirements

Per DSR, meta-requirements define the goals of a design theory (Walls et al., 1992) or a body of design knowledge, as developed in this study. The SSMRS meta-requirements describe high-level and somewhat open-ended characteristics that a social media recommender system *must* exhibit to be sensitive towards the user. We discuss the meta-requirements below in the order the Eval 2 interviewees have prioritised.

MR1 – Stakeholder Acceptance User acceptance is key to the success of SSMRS. To achieve this, SSMRS design must address users' needs for well-being enhancements. Research shows that social media users are particularly likely to accept a recommender system if it makes recommendations based on their current states of mind (Ayata et al., 2018; Polignano et al., 2021), as these recommendations are context-sensitive and can adapt to natural changes. While user acceptance is the primary focus of this study, it is important to also consider the needs of other stakeholders, such as social media providers and content creators. If the SSMRS design conflicts with business interests (e.g., all content recommended fails to generate financial compensation), its feasibility is compromised.

User and business-driven stakeholder needs often conflict. For instance, content such as edited and staged photos of influencers may generate profit for content creators, but consuming this type of content can harm users' well-being by fostering negative social comparisons. This can ultimately lead users to abandon the platform, reducing their value as customers and impacting the business interests of site providers and content creators. To avoid such outcomes, trade-offs in balancing stakeholder needs are crucial. The SSMRS approach is to focus on content that benefits users, which not only enhances user satisfaction and well-being, but also helps drive greater user engagement, creating long-term value for both users and business stakeholders.

MR2 – Individualisation SSMRS must consider each user individually to make custom recommendations that can foster their well-being. Although context awareness is an established recommender systems characteristic (Adomavicius & Tuzhilin, 2011; Adomavicius et al., 2011), the Eval 1 and Eval 2 interviewees reported receiving many static, infrequently adapting recommendations from the social media sites they used. SSMRS must capture the users' states of mind to make recommendations more dynamic, which can be achieved by exploiting existing data and knowledge (Jannach et al., 2010). Users' preferences and emotions change depending on the day of the week or time of the day, and so should dynamic recommendations. Additional, up-to-date personal data about the user (e.g., values, emotions, or current life circumstances) help individualise recommendations. However, obtaining this data is challenging because not all users share such data on social media (Beasley et al., 2016). Individualising recommendations further may positively affect stakeholders' needs besides users' well-being, for example, through increased profit resulting from a better customer fit.

MR3 – Data Privacy SSMRS must ensure data privacy. To make individual and dynamic recommendations, an SSMRS needs a significant amount of sensitive user data (Jaywant et al., 2016; Polignano et al., 2021). Owning such data is attractive to site providers and content creators. In addition to targeted advertising through recommendations (Jeckmans et al., 2013), they could be tempted to sell the data to third parties. Handing sensitive user data to third parties would contradict our notion of SSMRS. The stakeholders must keep the data confidential and only use it for sensitive recommendations. To ensure confidentiality, the site provider may be a data trustee to the content creators. As a result, content creators do not encounter sensitive user data, reducing the risk of data misuse. This meta-requirement intends to protect users who are not and those who are very concerned about their privacy, thus addressing the privacy paradox (Kokolakis, 2017). While this meta-requirement increases user acceptance, it may deter stakeholders keen to exploit sensitive user data beyond sensitive recommendations.

MR4 – Adverse Effect Mitigation SSMRS must anticipate and minimise risks that can occur, for example, from optimising recommender systems for engagement (Golbeck, 2020b). One such risk is users falling into filter bubbles (Elahi et al., 2022). SSMRS know which content recommendations will likely enhance users' well-being. However, unreflectively recommending content (e.g., biased news) risks users falling into filter bubbles. These filter bubbles can have adverse societal effects, such as increasing extremist opinions (Kitchens et al., 2020; Markgraf et al., 2019). Another risk is censorship. SSMRS know which content likely harms users' well-being. It would thus be reasonable not to recommend it. However, this must not result in a complete exclusion of specific themes. Critical world and personal events should not be excluded entirely from users' social media feeds. Drawing a clear line between sensitive recommendations and censorship is complex. It requires a constructive and socially ethical approach supported by the social media site providers.

4.5 Final Design Principles

With the initial meta-requirements as a basis, we developed six initial design principles of form and function (Gregor & Jones, 2007) that present exemplary ways of meeting the meta-requirements and refined them throughout the research process. The final design principles follow the anatomy of design principles described by Gregor et al. (2020); each includes an aim, a mechanism to achieve this aim, and a rationale.

DP1 – Be Transparent To ensure user acceptance, an SSMRS should transparently and concisely display how it derived recommendations. The transparency enables the site provider and content creators to demonstrate that an SSMRS complies with data privacy by only using data to make recommendations that the user has consented to the processing and that suit to foster their well-being. In addition, implementing DP1 can prevent the SSMRS from falling into the "uncanny valley," an effect triggering uneasy feelings among users known from the discipline of humanoid robotics (Mori et al., 2012). DP1 ensures user acceptance (MR1) and transparency in data privacy (MR3). The initial version of DP1 related transparency also to users' understanding of whether recommendations were good or bad. An Eval 2 interviewee remarked that this was not an SSMRS task. We, therefore, removed this quality from DP1.

DP2 – Allow Optionality To ensure user acceptance, an SSMRS should give the user the choice of whether and which individual sensitive data it uses to make individual, dynamic recommendations. This way, an SSMRS can make sensitive recommendations while considering users' safety needs and concerns. An optional complete deactivation of sensitive recommendations is also thinkable. Such a deactivation implied that the SSMRS made recommendations without sensitive data, for example, using coarse demographics only. As a result, the site provider and content creators can still operate their business and receive acceptance from users with privacy concerns. DP2, therefore, aims to meet the meta-requirements for stakeholder acceptance (MR1) and data privacy (MR3). The initial version of DP2 contained an option to turn off recommendations completely, as proposed by Eval 1 interviewees. However, as this quality would strongly conflict with the interests of social media site providers, we opted instead to deactivate sensitive recommendations.

DP3 – Enable user feedback To be able to make sensitive recommendations in the long term, an SSMRS should allow its users to give detailed feedback. By implementing this design principle, the SSMRS can maintain a user profile containing content that users do not want to see because it harms their well-being, or they want to see more often because it enhances their well-being. DP3 can also help users intervene if recommendations do not change over time and become irrelevant, which has been a problem so far, as reported in the Eval 1 interviews. It addresses the meta-requirements for stakeholder acceptance (MR1) and individualisation (MR2). The initial version of DP3 only suggested enabling feedback on content that harms users' well-being. The Eval 2 interviewees, however, stressed the importance of enabling positive feedback. Consequently, we modified DP3 accordingly.

DP4 – Capture users' States of Mind To be able to make individual sensitive recommendations, an SSMRS should dynamically capture its users' current states of mind. A user's state of mind includes their desire, values, or emotions. The SSMRS should know the users' beliefs, interests, likes, and dislikes, which continuously change. The SSMRS should thus capture states of mind as frequently as possible. Machine learning techniques can capture the necessary data from social media content, such as texts (Brady et al., 2022; Eichstaedt & Weidman, 2020). The data representing a user's state of mind must be reliable and valid because it ensures that the user perceives recommendations as sensitive, resulting in enhanced well-being. DP4 addresses the meta-requirement for individualisation (MR2). The initial version of DP4 was named "recognize individual state." We renamed it because Eval 2 interviewees considered this title unclear.

DP5 – Recommend Versatile Content To ensure that sensitive recommendations are responsible towards users, an SSMRS should recommend versatile content. Recommending certain content types, such as on global crises or bereavement of close ones, may be responsible despite (short-term) adverse effects on users' well-being. Given that an SSMRS did not recommend such content at all, users ran the risk of experiencing censorship or falling into filter bubbles. However, SSMRS should limit potentially harmful content in amount and present it as sensitively as possible. For example, an SSMRS could select content that deals with disasters or death objectively and non-emotionally. DP5 addresses the meta-requirements for individualisation (MR2) and adverse effect mitigation (MR4). The initial version of DP5 was named "hide content." Virtually all Eval 2 interviewees rated this title inappropriate because it suggested the deliberate concealment of contents, and we changed it accordingly.

DP6– Enhance Well-being To ensure that sensitive recommendations are responsible towards users, an SSRMS should prioritise content that directly supports users' well-being and mental health. This can be achieved through context-aware and relevant recommendations tailored to uplift users, such as humorous content like light-hearted memes or funny videos to improve mood, inspirational or educational material like life hacks or wellness tips, or positive updates like good news stories. By delivering such content that aligns with users' current emotional states and needs, an SSMRS can foster a sense of positivity, promote mental health, and create a more meaningful and supportive user experience. In addition to promoting well-being through uplifting and supportive content, this design principle serves a second purpose: as DP5 asserts, the responsible use of SSMRS disallows blanket blocking of all content that might harm users' well-being. DP6's mechanism intends to make for compensation in this regard. Since SSMRS must not shield users from all negative news or content, it appears appropriate to recommend content to directly enhance well-being. When social media use enhances their well-being, it also increases the likelihood of them spending more time on social media sites. This effect aligns with the site provider's and content creators' needs. DP6 addresses the meta-requirements for individualisation (MR2) and adverse effect mitigation (MR4). The initial version of DP6 did not relate to the site provider's and content creators' needs. We added this relation due to an Eval 2 interviewee's suggestion.

5 Functional Design and Evaluation

5.1 Functional Design Methodology

We complemented the presented conceptual artefacts (conceptual framework, meta-requirements, and design principles) with a set of design features as a functional artefact. We derived 15 initial design features deductively from the results of SLR-2. To this end, we searched the databases Scopus (title, abstract, and keywords; using the litbaskets.

io IS journal basket "M"), ACM Digital Library (title), and iEEE xPlore (title) with the search query *(("well-being" OR "well-being") AND "design") OR (("well-being" OR "well-being") AND "recommender") OR ("design" AND "recommender")*. To maintain a manageable result set while prioritising up-to-date insights, SLR-2 focused on studies published from 2013 onwards. This approach balances feasibility with comprehensiveness, ensuring our analysis reflects recent advancements while indirectly capturing foundational concepts through their inclusion in newer research.

The search process yielded 433 hits, which we subjected to an abstract screening to identify studies potentially relevant to our refined design principles. Articles were included in the result set if they suggested potential design features linked to at least one principle. This screening narrowed the set to 31 articles, which we analysed in detail to uncover potential design features. To further enhance the search, we employed forward searches (identifying articles citing the selected works), backward searches (examining references in the selected works), and complementary searches (exploring related keywords). These additional efforts identified 11 more articles, bringing the total to 42 articles (details on the articles in Supplementary Material D). From these, we extracted potential design features, clustered them based on the refined design principles, and summarised the features within each cluster, resulting in 15 initial features without any predefined number in mind (details on the initial features and clusters in Supplementary Material E).

In addition to deriving the design features in the construct activity, we refined the initial meta-requirements and design principles based on the actionable feedback from Eval 2, as discussed earlier. The refinements primarily involved rewording to enhance clarity and conciseness. However, a significant change was the creation of a separate meta-requirement for data privacy, which had previously been combined with the stakeholder acceptance meta-requirement.

5.1.1 Scientific Focus Group (Eval 3)

The initial design features, along with the refined meta-requirements and design principles, were used as input for Eval 3, which was conducted using a scientific focus group. We planned this focus group following the remarks on confirmatory focus groups in DSR by Hevner and Chatterjee (2010) and recruited eight researchers from a German IS research centre as participants. The focus group lasted approximately 60 min. We conducted it remotely using a video conferencing tool and recorded and transcribed it for analysis. We prepared a digital whiteboard containing the necessary descriptions of the schedule and contents and space for digital Post-its on which the participants and moderators could leave notes. One research team member led the focus group, while a second member took notes and ensured the agenda was adhered to and all topics discussed at a balanced time.

The focus group consisted of two parts. In the first part, lasting for approximately 15 min, participants reviewed the refined meta-requirements and design principles to familiarise themselves with the conceptual foundations of our research—an essential step for evaluating the initial design features. We then asked the participants to assess the clarity, comprehensibility, level of detail, and completeness of the refined meta-requirements and design principles using Post-its on the digital whiteboard. This process served as a second evaluation step to validate these artefacts. The output of this first part of Eval 3 was the validation of the meta-requirements and design principles, as participants identified no significant need for changes.

In the second part of the focus group, lasting for approximately 40 min, we presented the participants with the 15 initial design features. We asked them to evaluate the features using the criteria proposed by Sonnenberg & vom Brocke (2012a): feasibility, suitability, ease of use, effectiveness, clarity, and level of detail. We also asked the participants to reflect on the completeness of the design feature set (i.e., whether they missed a particular feature) and for specific changes. The second part of the focus group was a group discussion, which one research team member moderated, and the second jotted down all remarks on Post-its and organised them thematically on the digital whiteboard. To conclude the focus group, we asked each participant to rank the initial features by assigning three stars on the digital whiteboard, including the possibility of assigning multiple stars to one feature. Details of the focus group procedure are provided in Supplementary Material E.

The focus group results, serving as the second output part of Eval 3, were essential in refining the initial design features. This refinement process constituted the use activity of the present DSR study, in which we systematically transformed the 15 initial features into 11 refined ones by incorporating specific suggestions from individual participants and capturing key trends from the group discussion. Key adjustments included combining two features related to visual and semantic explanations into a single feature, revising a data privacy feature to adopt the opt-out paradigm, as participants believed an opt-in policy would likely be rejected by social media providers, and removing a feature on on-device data processing for being overly technical. Additionally, we merged two features addressing structured feedback, renamed features on verbal and non-verbal data analytics to behavioural and content analytics for clarity, dropped a feature on "bittersweet" recommendations

(Lustig et al., 2022) due to negative feedback, and reclassified a feature from surprising recommendations to serendipitous recommendations to align more closely with its original intent. Table 2 summarises the refined design features and their brief descriptions.

5.1.2 Kano Survey (Eval 4)

The refined design features served as input for Eval 4. To evaluate them, we set up an online survey based on the Kano customer satisfaction model (Kano et al., 1984). The Kano model categorises features into five quality categories that can either satisfy, dissatisfy, or leave customers—social media users in our study—indifferent: (1) *must-be* quality features do not lead to customer satisfaction when present, but to dissatisfaction when absent; (2) *one-dimensional* quality features suggest a proportional relationship between their fulfilment and customer satisfaction; (3) *attractive* quality features lead to high levels of customer satisfaction when present, with no negative impact when absent; (4) *reverse* quality features suggest an inversely proportional relationship between their fulfilment and customer satisfaction; (5) *indifferent* quality features do not affect customer satisfaction whether they are present or not (Matzler et al., 1996). Determining the quality to which a feature belongs involves asking one functional and one dysfunctional question (C. Berger et al., 1993). The functional question asks how the respondent felt if a given feature was present in a product with the non-scaled answer set *{"I like it that way."; "It must be that way."; "I am neutral."; "I can live with it that way."; "I dislike it that way."}*. The dysfunctional question asks how the respondent felt if the same feature was absent in the product using the same answer set. The feature quality results from inserting the answers to the two questions into the bivariate function K in Table 3. The *questionable* feature quality implies that the answers to the functional and dysfunctional questions will not yield a meaningful result regarding the five quality categories mentioned above. Previous Kano model research recommends having participants complete a self-stated importance (SSI) questionnaire in parallel to the Kano survey as an additional aid to identifying the most important features (C. Berger et al., 1993; Matzler et al., 1996). The SSI questionnaire measures how important the participants consider each feature to be on a seven-point scale ranging from "not at all important" to "extremely important."

Participants and preparation Before recruiting participants, we pre-tested the questionnaire with 16 uncompensated volunteers from a German IS research centre. We asked them for feedback on technical issues and the comprehensibility of the contents and estimated the time required to complete the survey. After making minor changes to the survey texts based on the feedback, we recruited US residents between 18 and 100 who indicated using social media via the online panel provider Prolific until reaching 249 completes. The survey had received ethical approval from the ethics committee of the University

Table 2 Brief descriptions of the 11 refined design features

	Refined design feature	*Brief description*
DF1	Visual semantic explanations	Visual semantic explanations expose the reasons for recommending specific content through concise texts and visual elements
DF2	Privacy hub	A privacy hub provides information on what sensitive data the social media site collects, what it is for, where it is stored, and the user's rights
DF3	Opt-out policy	An opt-out policy regarding sensitive data enables users to exclude specific data types from being considered for (sensitive) recommendations
DF4	Structured feedback	Structured feedback enables users to assess content recommendations in a structured manner (e.g., binary or ordinal scaled)
DF5	Conversational feedback	Conversational feedback enables users to assess content recommendations in a conversational manner in natural language
DF6	Behavioural analytics	Behavioural analytics is the anonymous analysis of user behaviour (e.g., reacting to or sharing posts) to capture their states of mind
DF7	Expert recommendations	Expert recommendations, curated by an editorial team for larger user groups, ensure content diversity in users' feeds
DF8	Serendipitous recommendations	Serendipitous recommendations allow users to discover new interests and aim to ensure content diversity in their feeds
DF9	Animal content	Animal content recommendations such as cute and funny images and videos of the users' favourite animals aim to enhance their well-being directly
DF10	Light-hearted content	Light-hearted content recommendations such as memes, jokes, or good news that match the users' preferences aim to enhance their well-being directly
DF11	Content analytics	Content analytics is the anonymous analysis of user-generated content (e.g., text, voice, or video messages) to capture their states of mind

Table 3 Kano evaluation function (adapted from C. Berger et al., 1993)

K(f, d)		*Dysfunctional answer d*				
		I like it that way	It must be that way	I am neutral	I can live with it that way	I dislike it that way
Functional answer f	I like it that way	Q	A	A	A	O
	It must be that way	R	I	I	I	M
	I am neutral	R	I	I	I	M
	I can live with it that way	R	I	I	I	M
	I dislike it that way	R	R	R	R	Q

M, must-be; *O*, one-dimensional; *A*, attractive; *R*, reverse; *I*, indifferent; *Q*, questionable

of Hohenheim. The median response time was 14.75 min. We followed Prolific's compensation recommendation, which led us to a compensation of USD 2.86 for each participant. The participants' mean age was 39.7 (SD = 12.6). The gender distribution was 55% male, 44.6% female, and 0.4% preferred not to say.

Procedure The survey started with explaining the nature of the functional and dysfunctional questions and response options as part of a comprehension check to ensure that participants understood which response option corresponded to their actual assessment. The participants had two chances to get the comprehension check right. If they failed the check two times, they had to return their submission. After passing the comprehension check, the participants were presented successively with the 11 refined design features in random order to prevent question order bias. The presentation of each feature included a brief textual description, an illustrative mobile screen mock-up, the functional Kano question, the dysfunctional Kano question, and the SSI question. After the fourth and eighth features, the participants were presented with an in-between screen showing a social media fun fact to temporarily reduce the cognitive load of the repetitive question answering. To conclude the questionnaire, the participants answered the affinity for technology interaction (ATI) short scale (ATI-S; Wessel et al., 2019) and a set of questions to characterise their social media use intensity (SMU), which we adopted from a study on social norms and expressions of sympathy in social media (Graf-Drasch et al., 2023). We included two attention checks in the questionnaire (Prolific, 2023): first, a nonsensical item, asking the participants to indicate their agreement with the statement *"Social media is a mountain in Alaska"* on a four-point scale (strongly disagree, disagree, agree, strongly agree); second, an instructional manipulation check in which participants had to select a specific option on a seven-point scale. The attention checks were displayed in the same place for every participant, regardless of the question randomisation. More details on the survey contents are provided in Supplementary Material F.[2]

Analysis The Kano analysis aimed to determine the quality category for each of the 11 refined design features. To achieve this, we first calculated the statistical mode m for each feature, identifying the most frequently assigned category from the function K based on participant responses. Recognizing that the second mode s (i.e., the second most frequent category) could be close in frequency to m, potentially leading to ambiguity, we conducted a Chi-square test (at a 95% confidence level) to assess the significance of the difference between m and s, as outlined by Schaule (2014).

If the difference was statistically significant, m was assigned as the feature's quality category. For cases where the difference was not significant, we applied the $(A, O, M) > (I, R, Q)$ rule proposed by C. Berger et al. (1993). This rule is applicable when $m \epsilon \{A, O, M\}$ and $s \epsilon \{I, R, Q\}$ (see Table 3 for category abbreviations). Using this approach, the function R determined the feature's quality category by prioritising the dominant group (either $\{A, O, M\}$ or $\{I, R, Q\}$) as follows:

$$R(A, O, M, I, R, Q) = \begin{cases} argmax\,(A, O, M) & if A + O + M > I + R + Q \\ argmax\,(I, R, Q) & otherwise \end{cases}$$

Results Table 4 displays the results of applying function K to participants' functional and dysfunctional responses, shown as both absolute and relative values. Each row in the left-hand section of the table totals $n = 249$ responses, while each row in the right-hand section sums to 100%. The

[2] In addition to Supplementary Material F, a complete set of survey screenshots is available at https://figshare.com/s/78207099ab0837f51f45; the dataset obtained by the survey is available at https://figshare.com/s/795931f386ecc80b552f

Table 4 Absolute (left) and relative distribution (right) of the quality categories to the refined design features

Refined design feature		*Absolute*						*Relative (in per cent)*					
		A	*O*	*M*	*I*	*R*	*Q*	*A*	*O*	*M*	*I*	*R*	*Q*
DF1	Visual semantic explanations	82	20	9	91	36	11	32.93	8.03	3.61	36.55	14.46	4.42
DF2	Privacy hub	23	57	112	43	5	9	9.24	22.89	44.98	17.27	2.01	3.61
DF3	Opt-out policy	22	54	116	39	5	13	8.84	21.69	46.59	15.66	2.01	5.22
DF4	Structured feedback	64	34	15	102	25	9	25.7	13.65	6.02	40.96	10.04	3.61
DF5	Conversational feedback	77	28	13	87	36	8	30.92	11.24	5.22	34.94	14.46	3.21
DF6	Behavioural analytics	60	26	29	95	32	7	24.1	10.44	11.65	38.15	12.85	2.81
DF7	Expert recommendations	47	9	8	133	45	7	18.88	3.61	3.21	53.41	18.07	2.81
DF8	Serendipitous recommendations	76	17	10	97	39	10	30.52	6.83	4.02	38.96	15.66	4.02
DF9	Animal content	91	43	17	70	19	9	36.55	17.27	6.83	28.11	7.63	3.61
DF10	Light-hearted content	85	38	10	86	17	13	34.14	15.26	4.02	34.54	6.83	5.22
DF11	Content analytics	33	9	7	68	121	11	13.25	3.61	2.81	27.31	48.59	4.42

M, must-be; *O*, one-dimensional; *A*, attractive; *R*, reverse; *I*, indifferent; *Q*, questionable

final quality categories, derived using the above analysis, are presented in Table 4.

According to the Kano analysis, DF2 and DF3 are must-be qualities, DF9 and DF10 are attractive qualities, DF11 is a reverse quality, and DF1, DF4, DF5, DF6, DF7, and DF8 are indifferent qualities. However, note that the second mode s is "attractive" for all features categorised as an indifferent quality, meaning that the participants tended to assess them positively. In addition to each refined design feature's final category, Table 5 shows the participants' mean SSI score. We could determine the final categories without resorting to the SSI but performed a Fisher's exact test (Fisher, 1970) for each refined design feature to check whether the SSI correlated with the answers to the Kano questions. As expected, there was no significant difference for any feature (details in Supplementary Material F).

Additionally, we controlled the absolute results in Table 4 (left) for differences based on two control variables with Fisher-Freeman-Halton tests (Freeman & Halton, 1951) for every refined feature (details in Supplementary Material F). First, we compared groups after median-splitting the ATI-S scores at 3.75 (M = 3.82, SD = 0.96, Cronbach's α = 0.74, 6-point scale) and found significant differences with small effect sizes (according to Cohen, 1988) for DF1, DF2, and DF4. Second, we performed a median split of the SMU scores at 3.0 (M = 3.13, SD = 0.97, Cronbach's α = 0.83, 5-point scale) and found significant differences with small effect sizes for DF2, DF4, DF6, and DF11.

5.2 Final Design Features

The results of the Kano analysis (i.e., the output of Eval 4) informed the selection of the final design features. Respondents identified content analytics (DF11) as a reverse quality. Consequently, we revised DF11, now titled "No content analytics," to invert its original concept. This revision ensures that SSMRS explicitly exclude the identified reverse quality, thereby supporting user acceptance. A privacy hub (DF2) and an opt-out data processing policy (DF3) are must-be qualities, according to the respondents, confirming the need for data privacy (MR3) as a separate meta-requirement. The fact that respondents evaluated these two privacy-related features as must-be further explains the assessment of content analytics as a reverse quality: social media users do not want SSMRS to process sensitive information from text, voice, or video messages to make recommendations. The results further indicate that animal content (DF9) and light-hearted content (DF10) recommendations are attractive qualities. This evaluation is particularly favourable since these refined features meet MR4 and implement DP6, both of which describe the essential

Table 5 Results of the Kano analysis (including final categories)

Refined design feature		*Mode m*	*Second mode s*	*p-value (χ^2 test [a])*		*(A, O, M) > (I, R, Q) rule applicable?*	*Final Category*	*Self-stated importance*
1	Visual semantic explanations	I	A	0.452		yes	**I**	3.59
2	Privacy hub	M	O	<0.001	***	not necessary	**M**	5.95
3	Opt-out policy	M	O	<0.001	***	not necessary	**M**	6.15
4	Structured feedback	I	A	<0.001	***	not necessary	**I**	3.94
5	Conversational feedback	I	A	0.391		yes	**I**	3.69
6	Behavioural analytics	I	A	0.001	**	not necessary	**I**	4.00
7	Expert recommendations	I	A	<0.001	***	not necessary	**I**	3.34
8	Serendipitous recommendations	I	A	0.06		yes	**I**	3.61
9	Animal content	A	I	0.055		yes	**A**	3.99
10	Light-hearted content	I	A	1.0		yes	**A**	3.98
11	Content analytics	R	I	<0.001	***	not necessary	**R**	3.15

* $p<0.05$, ** $p<0.01$, *** $p<0.001$; $n=249$; [a] with Yates correction; *M*, must-be; *A*, attractive; *R*, reverse, *I*, indifferent

characteristic of SSMRS: fostering users' well-being. The respondents determined all other refined design features (i.e., DF1, DF4, DF5, DF6, DF7, DF8) to be of indifferent quality, suggesting that implementing these features in an SSMRS is not expected to affect user acceptance adversely. On the contrary, the participants tended to give positive assessments of all these features, categorising their second mode *s* as an attractive quality. Since the indifferent features do not conflict with user acceptance but are necessary to meet the meta-requirements and implement the design principles, we included them in the final design features.

To explore subgroup differences, we conducted analyses based on participants' ATI and SMU scores, identifying statistically significant differences in the assessment distributions of several refined design features (all with small effect sizes).

ATI Subgroup Analysis Variations in participants' ATI scores revealed significant differences in the assessment distributions for three features: DF1, DF2, and DF4. For the privacy hub (DF2), separate Kano analyses with the data of each subgroup showed no differences between participants with ATI above or below the median (details in Supplementary Material F); it remained a must-be quality. However, for visual semantic explanations (DF1) and structured feedback (DF4), subgroup analyses revealed these features as attractive for participants with above-median ATI, while participants with equal or below-median ATI considered them indifferent. This outcome suggests that users with higher ATI are generally more inclined towards specific technological features, consistent with existing findings (Franke et al., 2019).

SMU Subgroup Analysis Variations in participants' SMU scores revealed significant differences in the assessment distributions for four features: privacy hub (DF2), structured feedback (DF4), behavioural analytics (DF6), and content analytics (DF11). However, unlike ATI, separate subgroup Kano analyses found no distinct categorisations of these features between participants with SMU above or below the median (details in Supplementary Material F). This outcome indicates that while SMU influences the assessment of design features to a small extent, these differences do not impact the overall categorization of feature qualities in our study.

The final design features, along with illustrative screenshots from the Kano survey, are presented below (Figs. 3, 4, 5, 6, 7 and 8). Orange arrows in the screenshots highlight the UI elements specifically relevant to each feature.

DF1 – Visual Semantic Explanations SSMRS can implement visual semantic explanations to explain why specific content recommendations appear in users' feeds. The explanations comprise a concise textual description or a visual element, such as a chart or graph. We derived this feature from the literature, drawing inspiration from concepts like reasoning paths (Ma et al., 2023) or textual justifications (Wilkinson et al., 2021) for recommendations. DF1 enhances SSMRS transparency (DP1), supporting stakeholder acceptance (MR1). The Kano analysis indicates that most participants (91) view visual semantic explanations as indifferent to user satisfaction, though a significant number (82) find it attractive. This attractivity, particularly among more technologically inclined users, as confirmed by the ATI subgroup analysis, justified its inclusion in the final design features.

DF2 – Privacy Hub SSMRS can implement a privacy hub to be transparent about processing sensitive user data. The

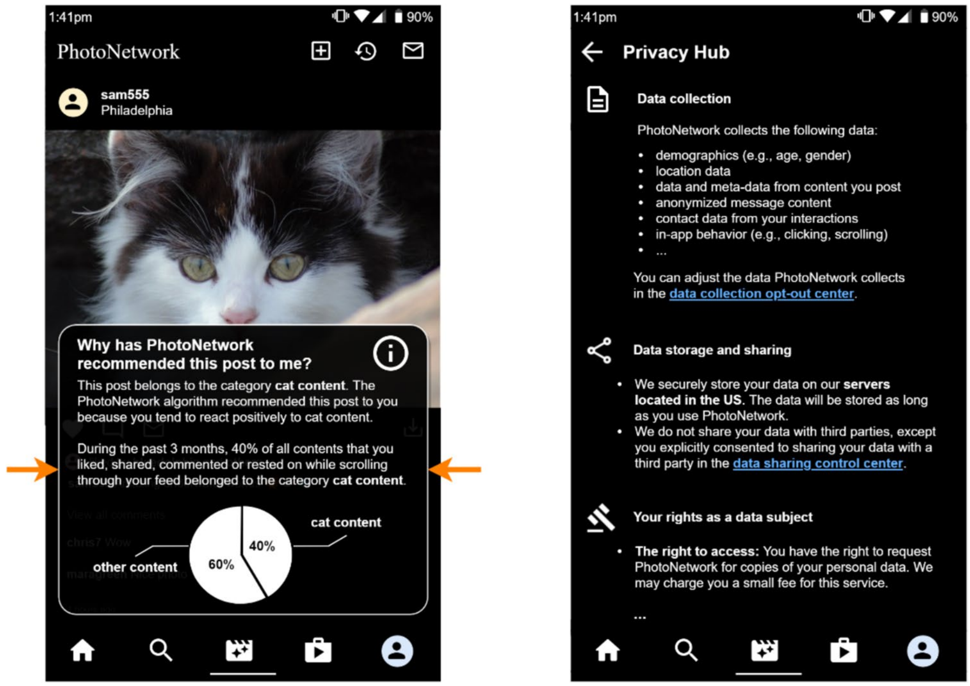

Fig. 3 Illustrative screenshots of DF1 (visual semantic explanations, left) and DF2 (privacy hub, right)

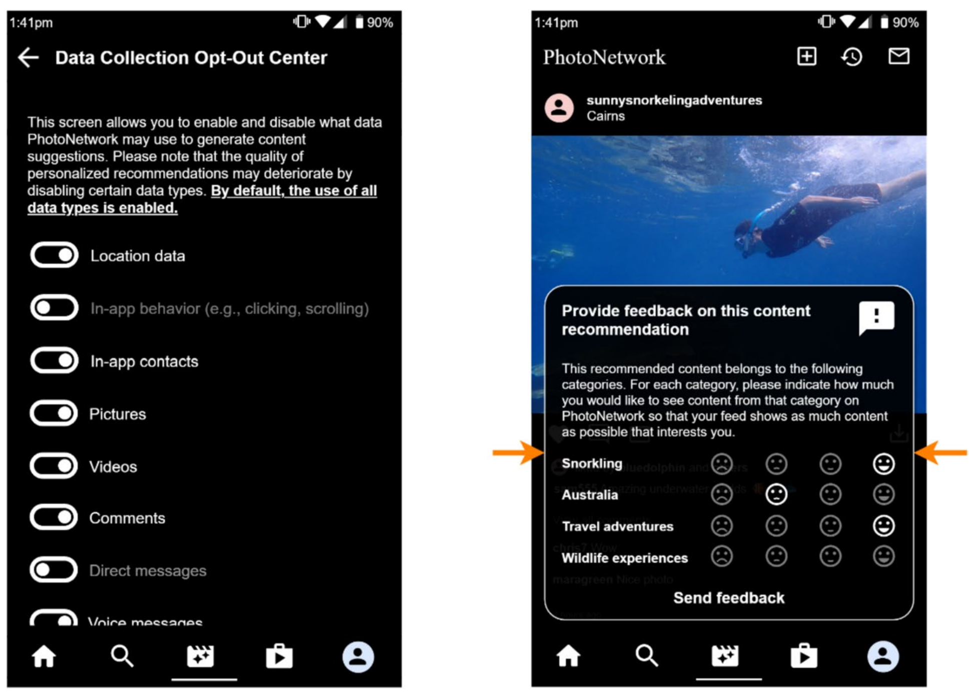

Fig. 4 Illustrative screenshots of DF3 (opt-out policy, left) and DF4 (structured feedback, right)

privacy hub indicates which data the SSMRS collects (e.g., behavioural or demographic data), for what purposes, and where the data is stored (i.e., server locations and providers) and informs users about their rights regarding the data. We adopted this feature from a study on transparency in news recommender systems (Storms et al., 2022). As DF1, DF2 makes SSMRS transparent (DP1) and benefits user acceptance (MR1). The Kano analysis supports the latter claim, categorising a privacy hub as a must-be quality.

DF3 – Opt-out Policy SSMRS can implement an opt-out policy regarding sensitive user data processing. An SSMRS will use all available data types by default to generate sensitive recommendations. Still, the users can exclude individual

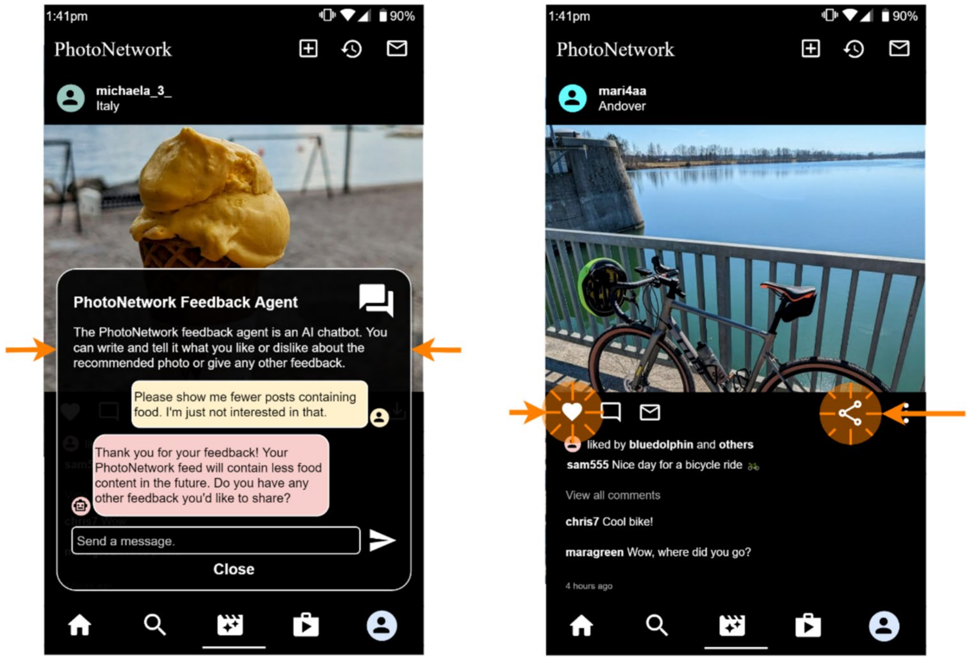

Fig. 5 Illustrative screenshots of DF5 (conversational feedback, left) and DF6 (behavioural analytics, right)

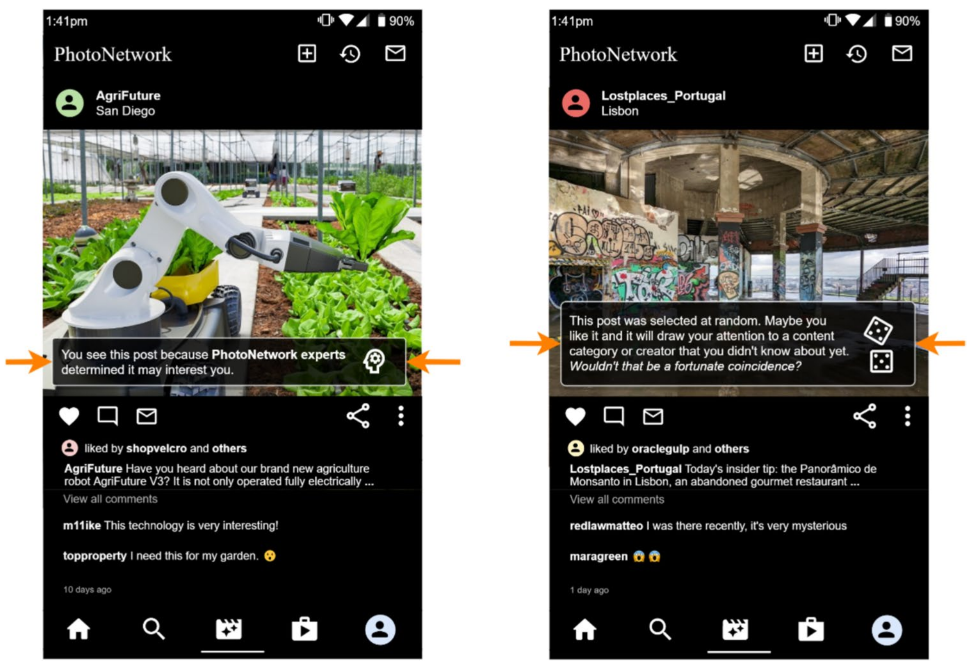

Fig. 6 Illustrative screenshots of DF7 (expert recommendations, left) and DF8 (serendipitous recommendations, right)

data types by deliberately deselecting them. In the literature, we found concepts for opt-in policies in recommender systems (e.g., Put et al., 2014). However, the focus group participants felt that social media site providers would not accept an opt-in policy. Instead, they proposed an opt-out policy, and we followed the suggestion. This way, DF3 still enables optionality (DP2) and benefits stakeholder acceptance (MR1) and data privacy (MR3). The Kano analysis supports the benefit regarding MR1, categorising an opt-out policy as a must-be quality.

DF4 – Structured Feedback SSMRS can allow users to give structured feedback on content recommendations, meaning that they can assess content recommendations within predefined limits such as in a unary (e.g., thumbs up), binary (e.g., like and dislike), or otherwise ordinal

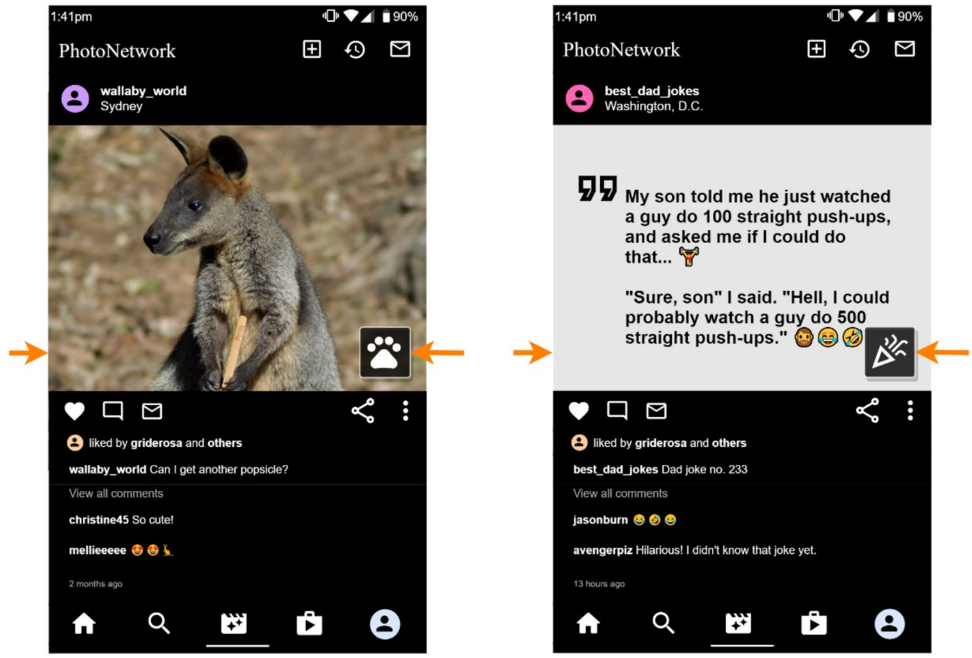

Fig. 7 Illustrative screenshots of DF9 (animal content, left) and DF10 (light-hearted content, right)

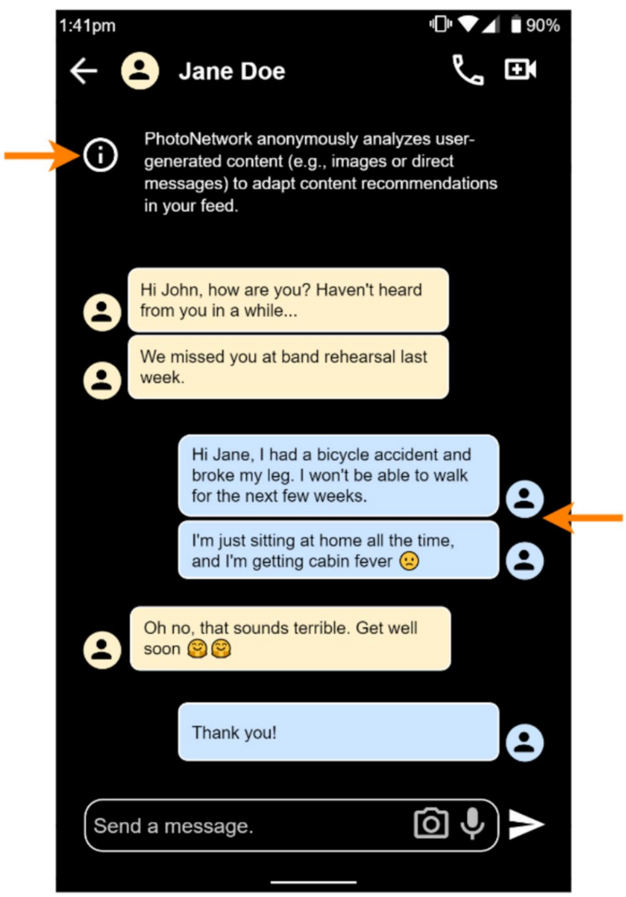

Fig. 8 Illustrative screenshot of DF11 (no content analytics)

scaled way (e.g., indicating satisfaction on a Likert scale). From a content perspective, structured feedback can reflect users' interest in specific categories. We derived this feature from the literature and used the weight-setting of categories as a model (e.g., Storms et al., 2022). The Kano analysis indicates that participants view structured feedback as indifferent but without a negative impact on user acceptance (MR1). The ATI subgroup analysis even classified DF4 as attractive for more technologically inclined users. Moreover, as DF4 implements DP3 and supports individualisation—a priority highlighted in the expert interviews during the conceptual design phase—it merits inclusion in the final feature set.

DF5 – Conversational Feedback SSMRS can allow users to give natural language feedback on content recommendations, for example, by communicating with an integrated artificial intelligence-based chatbot that can process and respond to the feedback. We derived this feature from the literature on conversational recommender systems (Jannach et al., 2022), one use case of which is feedback provision. DF5 enables user feedback (DP3) with a specific focus. While most participants (87) deemed its implementation indifferent to user acceptance, a notable number (77) found it attractive. Its inclusion in the final feature set is further supported by its link to individualisation (MR2) through DP3, reinforcing the priority highlighted during the conceptual design phase, similar to DF4.

DF6 – Behavioural Analytics SSMRS can anonymously analyse user behaviour, such as reacting to, commenting on, or sharing content or the time and frequency users spend looking at content to capture their state of mind. For example, an SSMRS may adopt design aspects of mobile stress assessment systems (Bonenberger et al., 2023) to use such behavioural determinants to detect when users experience increased stress levels and recommend content to soothe them. We derived this feature from the literature, drawing inspiration from a study on temporal-context user modelling in social media recommender systems (Yin et al., 2015). DF6 enables SSMRS to capture users' states of mind (DP4) and benefits individualisation (MR2). As the feature is not directly tied to user acceptance (MR1) via DP4 in the design knowledge, its classification as indifferent in the Kano analysis is not concerning. Moreover, like DF1, DF4, and DF5, its second mode was attractive, suggesting a favourable trend that justifies its inclusion in the final feature set.

DF7 – Expert Recommendations SSMRS can make recommendations curated by an editorial expert team for all users or large user groups (e.g., regarding age). An SSMRS should only intersperse such recommendations occasionally; otherwise, individualisation (MR2) would be lacking. However, expert recommendations can ensure diversity in users' feeds and thus reduce the risk of filter bubbles or otherwise biased recommendations. We adopted this feature from a study investigating the impact of expert curation in recommender systems (Herm-Stapelberg & Rothlauf, 2020). Like DF6, this feature is not directly linked to stakeholder acceptance via DP5, making its indifferent classification unproblematic. Its inclusion in the final feature set is justified by its role in addressing individualisation (MR2) and adverse effect mitigation (MR4), as emphasised by experts during the conceptual design phase.

DF8 – Serendipitous Recommendations SSMRS can make serendipitous recommendations, that is, content that does not match the users' previously identified interests but offers the chance to discover something new that can excite them. As with expert recommendations, an SSMRS should only occasionally make serendipitous recommendations. This recommendation type also aims to diversify users' feeds. We derived this feature from the literature, drawing inspiration from a study on surprising and oppositional recommender systems (Bauer & Schedl, 2017). As DF7, DF8 enables SSMRS to recommend versatile content (DP5). While its classification as indifferent in the Kano analysis does not suggest harm to user acceptance, its inclusion in the final feature set is justified by its potential to contribute to both individualisation (MR2) and adverse effect mitigation (MR4), particularly as users discover new and relevant content.

DF9 – Animal Content SSMRS can use animal content recommendations to enhance users' well-being directly. Social science research suggests positive effects between animals and human well-being and health (Wells, 2009). For people who enjoy animals, deliberately interspersing animal content into their feeds may positively impact their well-being. We derived this feature from a study providing evidence that dog content on social media led to significantly enhanced well-being compared to other content types (Golbeck, 2019). DF9 directly targets users' well-being (DP6). Social media users classified it as an attractive feature in the Kano survey. It further addresses the requirements of individualisation (MR2) and adverse effect mitigation (MR4).

DF10 – Light-hearted Content SSMRS can use light-hearted content recommendations to enhance users' well-being directly. Light-hearted content as to our notion includes memes, jokes, funny videos, good news, life hacks, or infographics. Light-hearted content will likely enhance users' well-being when matching their preferences. We drew the inspiration for this feature from a study investigating improving social media users' well-being through recommender systems (Golbeck, 2020a). Like DF9, DF10 targets users' well-being directly (DP6), has been classified as attractive in the Kano survey, and benefits individualisation (MR2) and adverse effect mitigation (MR4).

DF11 – No Content Analytics As discussed earlier, content analytics turned out to be a reverse quality in the Kano analysis, meaning its implementation would negatively impact user acceptance. This concept involved enabling SSRMS to anonymously analyse user-generated content, such as direct or voice messages or videos, to infer users' states of mind, drawing inspiration from research on user review-based sentiment analysis (e.g., Cai et al., 2022). Given its reverse quality, we decided to establish DF11 as a design feature but in an inverse form compared to its original representation in the Kano survey. This approach ensures that the reverse characteristic is excluded from the SSMRS.

Figure 9 below summarises the interplay between the design features, design principles, and meta-requirements, illustrating how these elements are interconnected and form the overall design knowledge.

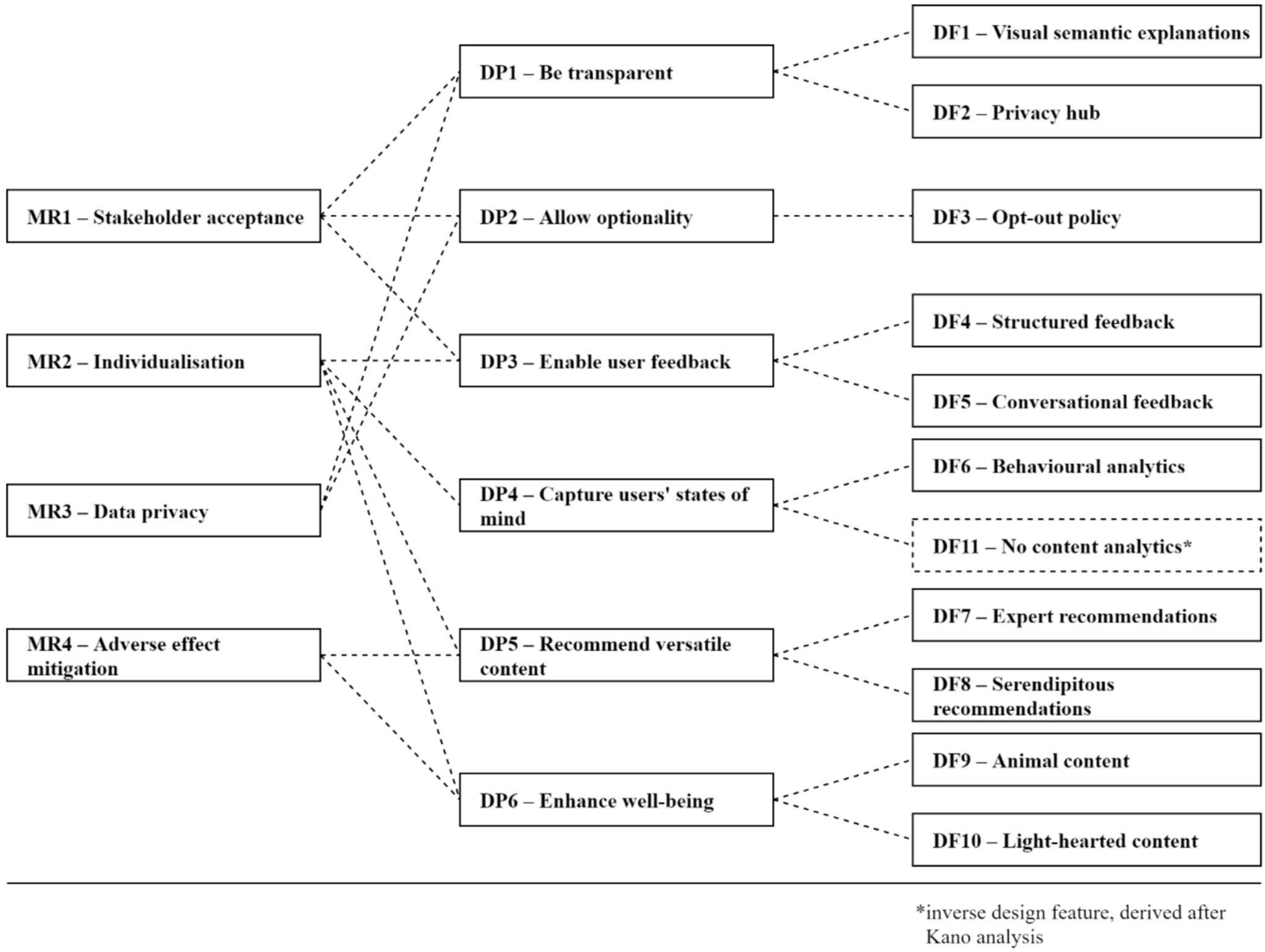

Fig. 9 Interplay of the meta-requirements, design principles, and design features

6 Discussion

6.1 Research Contributions

This study contributes to research in four ways. First, it enhances the understanding of why social media harms users' well-being and health in the context of recommender systems; that is, the study enhances the problem space. Previous work on social media implications on users' well-being and health investigated the impact of social media use from various perspectives, including social comparison (e.g., Mackson et al., 2019; Wirtz et al., 2021), user interactions (e.g., Verduyn et al., 2017; Yang, 2016), or usage extent (e.g., Ostic et al., 2021; Zhao, 2021). Our work builds upon relevant insights from this prior research, directing its focus through the lens of IS DSR, particularly addressing aspects pertinent to SSMRS. It also embraces the fundamental notion underlying the social impact guidelines for DSR by De Leoz and Petter (2018), conceptualising user impacts alongside those for other contextually related stakeholders. This study prioritises user needs in the problem space while acknowledging the relevance of other stakeholders, as reflected in the final conceptual framework, presented as a foundational design artefact. The feedback from Eval 1 and 2 complements the abovementioned literature insights to shape the final meta-requirements as a second design artefact, specifying how to address the problem space purposefully.

Second, building on the enhanced problem space, this study's primary contribution is a comprehensive, practice-based, and evaluated framework for designing SSMRS, conveyed through the final design principles and features as the third and fourth design artefacts. The final design principles, as principles of form and function (Gregor & Jones, 2007), offer conceptual guidance for designing any SSMRS. The final design features, as implementation principles (Gregor & Jones, 2007), provide functional guidelines exemplifying the implementation of an SSMRS following the final design principles. Together, these artefacts synthesise knowledge from expert feedback (inductively through the principles) and the literature (inductively through the principles and deductively through the features) into actionable theoretical design knowledge. This framework not only complements the IS literature on individual well-being and health at the intersection of social media and recommender systems but also establishes a tested foundation for future studies. Drawing inspiration from initial research advocating a more user-centric focus of social media recommender systems (Golbeck, 2020a, 2020b), our study pioneers this intersection with systematic and validated design knowledge, setting a benchmark for subsequent research on SSMRS.

Third, this work advances the research on responsible digitalisation, a research stream seeking to thwart the harmful consequences stemming from the pervasive influence of digital technologies in our daily lives while promoting positive effects (Recker et al., 2022). The SSMRS design knowledge integrates into the digital responsibility framework of Trier et al. (2023), which spans various principles and research themes on the personal, corporate, and societal levels. With SSMRS, we present a novel IS class that adheres to the following five digital responsibility principles by Trier et al. (2023): *functionality* and *norms/values* via an overarching ethical design focusing on user well-being, *data privacy* via MR3, *fairness* via MR4, and *transparency* via DP1. The SSMRS design knowledge further addresses three of the framework's research themes: *responsible media practices* by enabling a fairer and more regardful user experience (MR4), *responsible use of algorithms and AI methods* by introducing transparency (DP1) and optionality (DP2) to social media recommender systems, and *information privacy & security* by collecting and using sensitive user data exclusively for sensitive recommendations (MR3).

Fourth, this study contributes to DSR by being among the first to demonstrate the feasibility of Kano analysis as an evaluation method. The Kano analysis results proved exceptionally helpful in selecting the final design features. While we have not found explicit suggestions for using Kano analysis to evaluate functional design artefacts in the literature, we derived the suitability as follows: Sonnenberg & vom Brocke (2012a) refer to surveys in general as a suitable DSR evaluation instrument for all evaluation activities. Research on the Kano model further considers this method suitable for evaluating product features (e.g., Fong, 1996; Matzler et al., 1996). Both estimates combined imply that Kano analysis is well-suited to evaluate a functional DSR artefact resembling product features, such as our design features. In prior IS research, the Kano model has proved helpful in evaluating artefacts such as smart home app features (Berger et al., 2022) and proactive services features (Wenninger et al., 2022). Although not the case in either study, the Kano analyses would have also integrated well into a DSR project, which encouraged us to decide on this method in the present study.

6.2 Practical Implications

Regarding this study's implications for practice, we report the result of evaluating its practical relevance, present two key opportunities it implicates, and discuss three challenges, with the latter mainly affecting social media site providers and developers rather than users. We included an applicability check (Rosemann& Vessey, 2008) in the Eval 1 and 2 interviews to demonstrate the practical relevance of this research. An applicability check comprises the criteria of accessibility, importance, and suitability, which fully integrate into the evaluation criteria proposed by Sonnenberg & vom Brocke (2012a). At the end of Eval 1 and 2, all interviewees agreed that our research endeavour was important, accessible, and suitable for addressing the research problem, thus rendering it relevant to practice.

The most significant practical opportunity from the SSMRS design knowledge is to transform social media into a platform that is more sensitive towards users, thereby enhancing their well-being and health. By focusing on maximising users' well-being and mitigating adverse effects like depression caused by impaired well-being, social media can become a more genuinely social environment. This approach also calls for social media providers and content creators to adapt their business models towards prioritising user health and well-being, aligning with the fifth strategic direction of the World Health Organization's well-being and health promotion framework (World Health Organization, 2022). While this adaptation may require a shift from solely maximising user numbers and followers to fostering healthier user experiences, research suggests that well-being (e.g., Ganglmair-Wooliscroft & Wooliscroft, 2019; Zhong & Mitchell, 2012) positively influence consumption behaviour, meaning business profit interests may still be met or even exceeded.

A second practical opportunity is provided by the final design features, which serve as concrete, actionable guidelines for SSMRS designers and social media content creators. By implementing these features, designers and creators can actively contribute to enhancing user well-being and health through sensitive, context-aware, diverse, and relevant recommendations. The design features go beyond abstract principles by offering specific ideas, such as transparent explanations of recommendations, different feedback modes, and various forms of light-hearted content that uplifts users emotionally, promotes mental health, and supports resilience. Offering these actionable features ensures that the merged opportunity to make social media more sensitive and health-oriented becomes a tangible reality, bridging user-centred design and business feasibility.

While it is “the right thing” to prioritise social media users’ well-being and health, even with no anticipated long-term economic drawbacks, convincing site providers and content creators to act more sensitively presents an arduous challenge. Since addressing as many users as possible in as short a time as possible and engaging them as conveniently as possible, but, thus, insensitively, to earn money is expedient, persuading business stakeholders to prioritise user well-being will be a complex task.

A second challenge the SSMRS design knowledge poses is capturing users’ states of mind sufficiently frequently and in detail, as DP4 suggests. The fact that the Kano analysis results prohibit using sensitive user-generated content such as text, voice, or video messages to capture states of mind (DF11) exacerbates this challenge. SSMRS developers will have to rely on behavioural analytics (DF6) or publicly accessible content on social media sites to implement algorithms for capturing users’ states of mind.

A third challenge arises from MR4, requiring adverse effect mitigation, especially regarding whether an SSMRS should *not* recommend certain content. It is highly complex to walk the fine line between when a recommendation leads to well-being for a user and when it does not. One Eval 2 interviewee illustrated this complexity by posing whether it was good or bad for a user when they followed *“100 fitness Instagrammers”* because they could either suffer from social comparison or draw inspiration from the fitness content. Regarding this challenge, SSMRS developers must carefully and consistently evaluate whether and how specific implementation decisions affect social media recommendations and their consequences for users to ensure that the recommendations are sensitive.

6.3 Limitations

Our work is subject to limitations. First, beyond the evaluation activities we conducted, we did not implement a fully functioning SSMRS that adheres to the meta-requirements and design principles. We did not integrate the design features into a live social media site to test whether such an SSMRS effectively enhances users’ well-being. Given the complexities of implementing an SSMRS, amplified by the second and third challenges presented above, reporting such an endeavour adequately in a paper alongside the theoretical design knowledge appears too intricate. We, therefore, defer prototypical implementations of SSMRS into live social media sites and the corresponding evaluations regarding user well-being to future research endeavours. Second, our selection of databases limited the literature reviewed in SLR-1 and SLR-2 and, in the case of SLR-2, we only included literature from a set date onward. Therefore, we may have neglected works from other disciplines or earlier works that could have further enriched the design knowledge development process. Third, we attempted to recruit panels of experts from diverse, relevant disciplines for the Eval 1 and 2 interviews, allowing for a comprehensive evaluation of the research notion and the conceptual design artefacts. However, additional expert interviews in future research could enhance the design knowledge.

7 Concluding Note

This study presents design knowledge for SSMRS, comprising four design artefacts: a conceptual framework, a set of four meta-requirements, a set of six design principles, and a set of 11 design features. SSMRS have the potential to reduce the dark side of social media sites by making them more sensitive, turning them into virtual places that emphasise individuals’ well-being and health rather than perpetuating problems. Until this potential has been realised, users should disengage from social media if they feel that harmful effects of its use remain predominant. Making social media recommendations sensitive towards users makes it feasible to augment existing benefits and transform social media sites into tools that foster well-being and health on both individual and societal levels.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10796-025-10628-9.

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Authors' Contributions **Lukas Bonenberger (lead author):**
Significantly developed the research objective and research concept
Significantly planned and independently conducted the systematic literature reviews
Significantly planned and independently conducted the interviews
Planned and conducted the focus group together with Julia Zeller-Lanzl
Significantly planned and independently conducted the Kano survey
Independently transcribed the focus group
Independently processed the survey results
Selected and adapted the design science research process together with Julia Zeller-Lanzl
Independently coded and analysed the interviews
Independently coded and analysed the focus group
Significantly derived and refined design artefacts from the results of the structured literature reviews, interviews, and focus group
Significantly evaluated the survey results
Independently drafted the initial manuscript
Revised the initial manuscript draft together with Julia Zeller-Lanzl
Addressed the comments from the major revision together with Julia Zeller-Lanzl
Addressed the comments from the minor revision
Julia Zeller-Lanzl (secondary author):
Supported the development of the research objective and research con-

cept
Supported planning the systematic literature reviews
Supported planning of the interviews
Planned and conducted the focus group together with Lukas Bonenberger
Supported planning of the Kano survey
Selected and adapted the design science research process together with Lukas Bonenberger
Supported deriving and refining design artefacts from the results of the structured literature reviews, interviews, and focus group
Supported evaluating the survey results
Provided feedback for the first manuscript draft
Revised first manuscript draft together with Lukas Bonenberger
Addressed the comments from the major revision together with Lukas Bonenberger

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Data Availability The datasets generated by the Kano survey and analysed during the current study are available at https://figshare.com/s/795931f386ecc80b552f. The interview and focus group transcripts cannot be publicly shared in compliance with privacy regulations.

Declarations

Ethics Approval and Consent to Participate The Kano survey had received ethical approval from the ethics committee of the University of Hohenheim, Germany. All participants in the Kano survey, the focus group, and the semi-structured interviews gave informed consent before participation.

Consent for Publication All interview and focus group participants provided informed consent for their answers to be anonymously published.

Competing Interests Not appliable.

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