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Recommended to you: an experimental study of normative influences from algorithmic and social recommendations on social media

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Abstract

On social media, artificial intelligence (AI) increasingly curates content alongside social contacts. We examine whether social and algorithmic recommendations shape users' perceived social norms around a moral issue and their intentions to engage with it. Drawing on theories of human–machine communication, human–AI interaction, and social norms, this experimental survey ($N = 1{,}021$) compares social, algorithmic, and popularity-based algorithmic recommendations (e.g., "most read") in the context of digital immortality. Recommendation type did not affect perceived norms, and algorithmic appreciation did not moderate these effects. However, perceived social norms—especially norms attributed to one's social environment—were positively associated with intentions to discuss and act on the issue. These findings suggest that recommendations do not deterministically exert normative influence; they, however, also point to the potential power of perceived norms in shaping engagement with emerging moral and technological issues. Future research should investigate the conditions under which algorithmic and social cues shape normative perceptions and help further clarify the role of AI-driven content curation in public discourse.

Keywords Recommendations · Algorithms · Social contacts · Social media · Social norms · Experimental design

1 Introduction

The rise of artificial intelligence (AI) impacts public discourse by shaping which issues and viewpoints become visible and salient. This is particularly evident on social media—an essential space for public discourse (van Dijck et al. 2018)—where people encounter and interpret public issues even when they do not actively post or comment. Even passive exposure can be consequential, as users observe which topics attract attention and what forms of engagement appear common and socially acceptable.

On social media, content is increasingly curated not only by social contacts, such as friends, family, colleagues, and acquaintances, but also by AI-based algorithms (Thorson and Wells 2016). These two sources of content curation reflect distinct types of recommendations. *Social recommendations* refer to content that becomes visible because others in one's network share, like, or otherwise engage with it. *Algorithmic recommendations* refer to content suggested, ranked, or highlighted by AI-based systems based on user data and/or collective preferences. By determining what content people are exposed to, both recommendation types may influence normative perceptions of issue engagement, that is, which issues are perceived as normal and appropriate to engage with. These perceptions of what is socially expected can influence how people behave and, in turn, affect public discussions and social norms more broadly.

Scholars increasingly call for reconceptualizing and examining communicative influence in the age of AI (Dehnert and Mongeau 2022; Sundar and Lee 2022). Indeed, there is a growing body of research that explores how social and algorithmic recommendations influence how people perceive sources, form opinions and (intend to) act (Huang and Wang 2023). However, there is still a limited understanding of how social and algorithmic recommendations influence perceived social norms and subsequent action—especially in the context of moral debates, which are central to reinforcing shared values and informing ethical decision-making in

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societies. Furthermore, as people differ in how much they value and trust algorithms (Logg et al. 2019), the question arises as to whether the corresponding algorithmic appreciation moderates these normative processes. Understanding these dynamics is crucial for comprehending the broader implications of AI-based content curation on public discourse, as well as on the formation of social norms in society. Therefore, addressing this gap, contributes to a more comprehensive understanding of how communicative influence operates in algorithmic media environments.

This study examines how social and algorithmic recommendations affect perceived norms of engaging with moral issues on social media, that is, norms for discussing the issue of digital immortality and acting on that issue. To this end, we adopt a user perspective by examining how recommendations appear to users on social media, rather than analyzing the technical workings of the algorithms. By integrating theoretical perspectives from human–machine communication (Nass and Moon 2000; Sundar 2008) with recent work on human-AI interaction (Shin 2024, 2025) as well as social norms research (Cialdini et al. 1990; Rimal and Real 2005), we examine how different types of social and algorithmic recommendations affect people's perceptions of social norms and their willingness to act upon it. We distinguish between descriptive norms, referring to perceptions of how common a behavior is, and injunctive norms, referring to perceptions of social approval of that behavior (Cialdini et al. 1990). Additionally, we study whether these effects are moderated by individual algorithm appreciation. We do so in the context of digital immortality, a novel and morally complex topic. We test the hypotheses using an experimental survey design.

2 Literature review

2.1 Social and algorithmic recommendations on social media

On social media, content is curated and recommended to users primarily through two sources: social contacts and algorithms (Thorson and Wells 2016). Social contacts—humans to which an individual is connected, such as friends, family members, colleagues and acquaintances—can share media content on social media, influencing what others see. The significance of social recommendations has long been recognized in communication research, originating with the two-step flow model (Katz and Lazarsfeld 1955), and has since been reaffirmed in digital contexts, where peers and social network contacts play a critical role in shaping attitudes and behaviors (Bakshy et al. 2012; Messing and Westwood 2014). By sharing and endorsing content, peers and social networks convey normative information about what others attend to and approve of—particularly in social media where endorsements (likes or shares) are visible and easily quantified (Geber and Hefner 2019). With the rise of AI—broadly defined as computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, and decision-making (Russell and Norvig 2021)—algorithms have become another major source of recommendations (Sundar and Nass 2001; Thorson and Wells 2016). An algorithm can be defined as a finite, step-by-step set of computational rules or procedures for solving a problem or accomplishing a specific task (Cormen et al. 2009). In the literature on communicative AI, such algorithms are often referred to as AI curators—technological agents that select and present content (Sundar and Lee 2022). Recommender algorithms personalize content by filtering, rating, and curating it based on user behaviors and preferences (Roy and Dutta 2022). Beyond personal preferences, algorithms also employ collaborative filtering, a technique that takes into account the behaviors of similar users to surface popular or trending content (Roy and Dutta 2022).

Rather than focusing on the technical functioning of algorithms, this study focuses on how recommendations are presented, and how this presentation influences users. From this perspective, we define three types of recommendations on social media: (1) Social recommendations that are typically attributed to a specific social contact (e.g., "recommended by [name]"). (2) Algorithmic recommendations that refer to content labeled as generated by an algorithm (e.g., "algorithmically recommended"). (3) Popularity-based algorithmic recommendations that refer to content suggested through collaborative filtering and are explicitly marked as popular or trending (e.g., "Most read").

2.2 Effects of social and algorithmic recommendations on social media

An increasing number of empirical studies compares the communicative effects of algorithmic versus human recommendations (Huang and Wang 2023). Overall, Huang and Wang's (2023) meta-analysis of 121 experimental studies found no clear differences in communicative influence between AI agents and humans, including effects on perceptions, attitudes, intentions, and behaviors.

Most outcomes measured relate directly to the recommendation itself, often assessing how the recommendation is perceived. Specifically, many studies report a relative rejection of algorithmic suggestions—known as *algorithm aversion* (Dietvorst et al. 2015)—in areas such as jokes (Yeomans et al. 2019), online shopping (Chen et al. 2024), health services (Longoni et al. 2019), hiring (Ochmann et al. 2020), and fairness judgments (Bigman and Gray 2018; Jauernig et al. 2022). Some other studies find higher *appreciation* of AI-based recommendations (Logg et al. 2019; You et al.

2022). Crucially, perceptions of AI-based recommendations vary depending on what is measured—trust, credibility, competence, or likeability—and the context (Sundar and Nass 2001; Tolmeijer et al. 2022). Further recent discussions emphasize a calibration perspective in which users dynamically adjust reliance on algorithmic systems based on contextual cues, perceived goals, and perceived legitimacy. Shin (2025) conceptualizes algorithmic appreciation as a cognitive and ethical process rather than a fixed attitude, linking perceived legitimacy and value alignment to users' willingness to rely on AI-mediated judgments. Apart from such context-dependent evaluations of recommendations, however, there appear to be individual differences in the extent to which people generally value algorithms (i.e., algorithmic appreciation) that need to be considered (Gran et al. 2021; Mahmud et al. 2022).

Ultimately, there are hardly any studies that deal with the effect of social and algorithmic recommendations in social media on perceived social norms, specifically in the context of emerging moral debates. This gap matters, because algorithmic recommendations can contain implicit and explicit normative information (e.g., "most read") and may therefore *provide* cues that users use when forming normative perceptions. These effects could have a significant influence on moral discourse and corresponding norms at the societal level.

2.3 Theoretical framework

To examine how social and algorithmic recommendations on social media, we integrate human–machine communication (Nass and Moon 2000; Sundar 2008; Gambino et al. 2020) and human-AI interaction (Shin 2024, 2025) with theories on social norms (Cialdini et al. 1990; Rimal and Real 2005; Rimal and Lapinski 2015). These frameworks capture both the technical and social aspects of recommendations on social media.

Theories on technology influence. Our first theoretical perspective basically builds on the *computers are social actors* framework (CASA, Nass and Moon 2000; Reeves and Nass 1996) and the *modality, agency, interactivity, and navigability* model (MAIN, Sundar 2008). Both emphasize that technology's influence is not inherent but rather depends on the cues users perceive and interpret, which activate heuristics that shape their responses (see also Fiore et al. 2013). Specifically, the CASA paradigm states that users mindlessly and naturally treat computers as if they are humans (Reeves and Nass 1996; Nass and Moon 2000). Nass and Moon (2000) highlight that people of course understand that computer are not human, but that they still show social responses to them. This response is triggered by social cues embedded in technology, which lead users to apply the same heuristics as in human interactions (Nass and Moon 2000). Cues are features that are salient to users "because of their potential as channels of useful information" (Fiore et al. 2013).

In a similar way, the MAIN model (Sundar 2008) applies a heuristic approach to understanding technology effects. It highlights the importance of cues that trigger a series of heuristics which ultimately influence perceptions of quality and source credibility. A heuristic, which is a judgmental rule (Sundar 2008), might lead to a snap judgment in heuristic processing. However, it might also be helpful as analytical tools while processing systematically. Acknowledging the technological developments, the CASA (e.g., Gambino et al. 2020; Lombard and Xu 2021) and the MAIN (e.g., Sundar et al. 2015) have been refined over the years.

Complementing both models, recent work treats algorithmic curation as part of the epistemic infrastructure of digital environments, shaping what users encounter as truthful and relevant (Shin 2024). In such environments, indicators like "most read" invite users to infer what others notice and what matters. Building on this perspective, trust in algorithms can be understood as an ongoing process in which users cognitively and ethically calibrate their reliance on algorithmic systems, asking whether these systems appear legitimate, fair, and aligned with their own values (Shin 2025). In this sense, recommendation cues function as signals through which users connect informational authority to questions of legitimacy and normativity. Ultimately, the influence of algorithmic recommendation depends on how users read recommendation cues as social cues about what others attend to and approve of.

Theories on normative influence. By activating social heuristics, algorithmic recommendations might influence normative perceptions of what others do and approve of, thereby shaping individual action. Theories on normative influences, such as the *focus theory of normative conduct* (FTNC; Cialdini et al. 1990) and *theory of normative social behavior* (TNSB; Rimal and Real 2005), help understanding such normative effects. They suggest that human action is guided by perceptions of social norms. Two aspects of norms need to be differentiated (Deutsch and Gerard 1955), that is, perceived descriptive norms and thus perceptions about the prevalence of a behavior and perceived injunctive norms, that is, perceptions of the social approval of a behavior. People tend to conform to social norms because they want to do the right thing and act in a socially approved way to avoid negative social sanctions (Cialdini et al. 1990). Social norms refer to specific reference groups that are closer or further away in the social relationship. The closer an individual feels to a reference group, the stronger its influence, as identification and the desire to belong to the group increase (Neighbors et al. 2008).

While most theoretical work on social norms has focused on understanding the downstream influences of perceived norms on individual behavior, more recent theoretical work

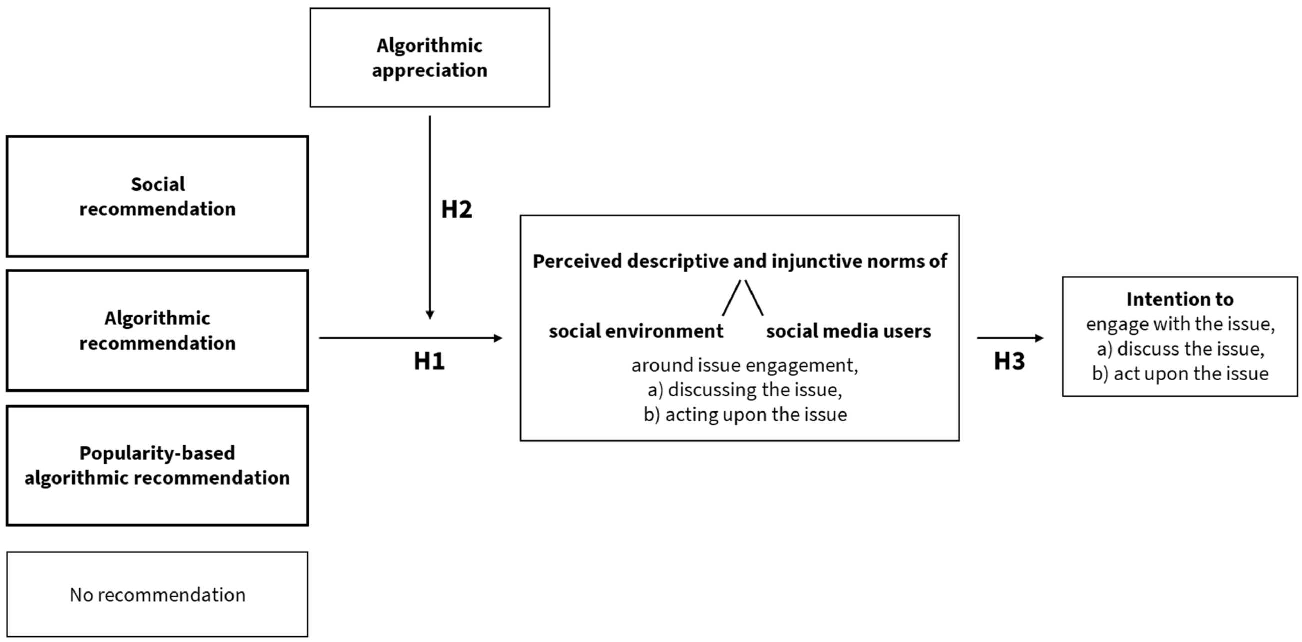

Fig. 1 Overview on hypotheses

has addressed the question as to how perceptions of norms are shaped in digital media environments (Yanovitzky and Rimal 2006; Rimal and Lapinski 2015). This work highlights that social cues in digital media environments—such as popularity indicators—convey social information about the approval and prevalence of a behavior and thereby affect normative perceptions (Geber and Hefner 2019). Applied to social and algorithmic recommendations, this means that recommendations inherently carry normative information: If something is recommended, it is likely prevalent and socially approved among social referents. Collaborative filtering is particularly relevant here, as it not only implicitly but *explicitly* conveys popularity cues (e.g., "Most read"). However, the role of algorithmic recommendations in shaping normative perceptions and influencing action remains an underexplored area of research.

3 The present study and hypotheses

This study investigates how social media posts on moral issues that are socially or algorithmically recommended affect users' perceptions of social norms and their intentions to engage with issues. Engagement thereby encompasses discussing that issue online or offline as well as taking (private or political) action on that issue that may support or challenge it.

To test these effects, we conducted an experiment with three recommendation conditions: (1) a social recommendation [condition 1] (2) an algorithmic recommendation [condition 2]; (3) a popularity-based algorithmic recommendation [condition 3]. In addition, we included a control condition in which the post appeared without being labeled as a recommendation. As a moral issue, we chose *digital immortality*—the idea that technology can enable interactions with a deceased person through chatbots, avatars, or other digital means. Given its novelty and ethical complexity, social norms of engagement with digital immortality are still developing (Galvão et al. 2021). This makes it a suitable case, as external cues may have more influence when attitudes are not yet firmly formed. We used two versions of the post on the issue of digital immortality, one endorsing and one opposing digital immortality, to ensure that the effects identified covers a range of moral evaluations of the topic. Figure 1 presents the normative influence process we assume, displaying the overall hypotheses that we derive and specify in the following.[1] All hypotheses were preregistered on OSF: https://osf.io/7mey3/?view_only=2e6dcc1b593442fdaf5a193924ea243d.

Building on theorizing in human–machine communication (Nass and Moon 2000; Sundar 2008) and more recent work on AI-mediated communication (Shin 2024, 2025), as well as social norms theory (Cialdini et al. 1990; Rimal and Real 2005), we assume that recommendations—whether social or algorithmic—may activate a social

[1] Please note that we have slightly adapted the wording of the hypotheses for the sake of better readability; the content of the hypotheses has not been changed.

heuristic, because they suggest that content is relevant to others (Sundar 2008). In this sense, recommendation labels (e.g., "recommended," "algorithmically recommended," "most read") do not merely label content; they frame why it is being curated and whether it should be treated as normatively informative (Shin 2025). Empirical work in digital contexts shows that social cues and endorsements shape what content users attend to and consider relevant (Bakshy et al. 2012; Messing and Westwood 2014; Zarouali et al. 2021). Social media cues such as endorsements and popularity indicators can also convey information about what others attend to and approve of, which can shape perceived descriptive and injunctive norms (Geber and Hefner 2019; Zarouali et al. 2022). Thus, posts labeled as "recommended"—across different sources—may be perceived as more socially relevant and as receiving more attention than non-recommended posts. We therefore expect recommendation labels to increase perceived norms of engaging with the issue.

H1) Participants exposed to a social or algorithmic recommended post [condition 1–3] on digital immortality will perceive higher social norms around engaging with the issue (i.e., discussing and acting upon the issue), compared to participants who were exposed to a non-recommended post [control condition].

Recommendation labels may imply different reference groups. Social recommendations explicitly link content to specific social referents (e.g., friends), making them particularly informative about what matters within one's immediate social environment (Bakshy et al. 2012; Zarouali et al. 2021). By contrast, algorithmic recommendations—especially when framed via aggregated behavior (e.g., "Most read")—more strongly suggest what is common among the broader population of social media users and should therefore be more diagnostic for perceived norms attributed to that wider group (Zarouali et al. 2022). This distinction motivates our expectations regarding differential effects on perceived norms of one's social environment versus perceived norms of social media users.

H1a) A socially recommended post [condition 1] has stronger effects on perceived social norms of the social environment around engaging with the issue than an algorithmically recommended post [condition 2, 3].

H1b) An algorithmically recommended post [condition 2, 3] has stronger effects on perceived social norms of social media users around engaging with the issue; with a popularity-based, algorithmically recommended post having the strongest effect on perceived social norms of social media users.

Existing empirical research shows meaningful variation in how people respond to algorithmic outputs. While some studies demonstrate algorithm aversion in multiple domains (Dietvorst et al. 2015), other work finds that people may rely strongly on algorithmic advice and that such reliance systematically depends on individual orientations toward algorithms (Logg et al. 2019; You et al. 2022). Therefore, beyond average effects, algorithm appreciation should condition the extent to which algorithmic recommendations are taken as informative signals and translated into perceived norms.

H2) The more the participants appreciate algorithms, the stronger the effects of algorithmic recommendations [condition 2, 3] on perceived social norms of the social environment and of social media users around engaging with an issue.

Finally, according to social norm theories (Cialdini et al. 1990; Rimal and Real 2005; see above), perceived social norms—both descriptive (what others do) and injunctive (what others approve of)—guide individual action, particularly in situations of uncertainty. Given the novelty of the topic of digital immortality and the associated uncertainty that people may face when evaluating it, social norms are likely to be particularly influential in providing guidance. We therefore assume that the stronger the perceived social norms, the higher the individual's intention to engage with that issue, that is, to discuss the issue and take action on it. In addition, we argue that norms related to one's personal social environment are likely to be stronger than those perceived from social media users as individuals feel more need to comply with proximate reference group (Neighbors et al. 2008). This leads to our final hypotheses:

H3) The higher the perceived social norms of the social environment and social media users around engaging with the issue, the higher the intention to engage with the issue.

H3a) The effects of the perceived social norms of the social environment around engaging with the issue are stronger than those of the perceived social norms of the social media users.

4 Methods

We conducted a between-subject design, including 4 different conditions of recommendations (i.e., social, algorithmic, popularity-based algorithmic, no recommendation) and 2 versions of a moral evaluation of the issue of digital immortality (i.e., endorsing, opposing digital immortality). The latter variation did not serve as a theoretically relevant factor but was sought to provide a more complete picture of the different moral evaluations that can be taken on the issue. We contracted with the research institute Intervista for data collection. The data collection started November 29 and was completed December 16, 2024. Before data collection, the questionnaire, design, and sampling strategy have been approved by the faculty's ethics committee. Data, analysis code, and the questionnaire are on OSF: https://osf.io/7dfbs/overview?view_only=3aff2d3f39ff40a78e9b216e26242727.

4.1 Sample

Participants were recruited from the online panel of the research institute. The target sample were social media users over the age of 18. We used interlocked quota according to gender and age and non-interlocked according to education to ensure a diverse sample of the population. The quota was based on current, population-representative specifications from the Swiss Federal Statistical Office (2023, 2024). The final sample comprised 1,021 participants, which is enough to detect small-sized effects in multivariate analyses of covariance with two factors and covariates (power = 0.80, effect size = 0.10, alpha error probability = 0.05). The average age was 44 years (*SD* = 16.36, range 18 – 79 years), and half of the sample was female (49%). The sample included people with varying education levels: 5% with compulsory education, 45% with vocational education and training, 12% with general training, 17% with professional education, and 22% with higher education. The distribution of sociodemographic characteristics closely follows the distribution in the population according to the Swiss Federal Statistical Office, except for education. Compared to the population, individuals with only compulsory education were underrepresented—a well-known challenge in survey studies.

4.2 Procedure

After giving informed consent, participants answered a series of questions about their sociodemographic characteristics, social media use, algorithmic appreciation and awareness as well as attitudes toward digital immortality. Participants were then randomly allocated to one of the eight conditions (i.e., 4 recommendations*2 moral evaluations) and exposed to the stimulus. Afterwards, participants were asked, in the following order, questions about perceived injunctive and descriptive norms of discussing the issue of digital immortality and acting on that issue as well as corresponding intentions. These questions were followed by questions serving the manipulation and validation check. The survey concluded with some questions on household size and household income and, finally, a debriefing. Participants received a standard compensation of the research company upon completion of the study.

4.3 Measurements

Social and algorithmic recommendations. The experimental design included 4 conditions of the recommendation of a post: (1) a social recommendation (labeled as "recommended by online friend"), (2) an algorithmic recommendation (labeled as "algorithmically recommended"), (3) a popularity-based algorithmic recommendation (labeled as "algorithmically recommended because most read"), (4) no recommendation. In every condition, we used a scenario to introduce the stimulus in which we highlighted the source of the recommendation before the post appeared: "Now imagine you are on a fictitious social media platform and the following online post is recommended to you by [an online friend/algorithm/algorithm because most read]".

We also included two versions of a moral evaluation of the issue: an endorsing evaluation that highlights the chances of digital immortality and an opposing evaluation that highlights the risks of digital immortality. An exemplary stimulus material is depicted in Fig. 2. The full material can be accessed on OSF: https://osf.io/7dfbs.

For the measurement of the dependent, moderator, and control variables, we used, if not indicated otherwise, a 7-point Likert scale ranging from 1 = "do not agree at all" to 7 "fully agree". Issue engagement was divided into a) discussing the issue and b) acting on the issue; accordingly, perceived social norms and intentions were measured for these two forms of issue engagement.

Perceived social norms of discussing the issue. To measure perceived social norms of discussing the issue and the intention to discuss the issue, we defined three stem items: "… to draw attention to the topic of digital immortality"; "… to share information on the topic of digital immortality"; "… to discuss the topic of digital immortality." Descriptive norms were operationalized as participants' perceptions of how common engagement with the issue is, whereas injunctive norms captured perceived social approval of such engagement (Rimal and Real 2005). Depending on the concept, we adopted the introduction to the items in accordance with these definitions and common norms measurements (e.g., Rimal and Real 2005; Friemel and Geber 2021; Sedlander et al. 2022). We combined these items to mean indices, if they were sufficiently internally reliable, as indicated by Cronbach's α.

The items to measure the *descriptive norms of the social environment* were introduced by "many of my social environment…" (α = 0.91; *M* = 2.40, *SD* = 1.39). Thus, an exemplary item to measure perceived descriptive norms of the social environment was: "Many of my social environment draw attention to the topic of digital immortality." For the *injunctive norms of the social environment,* we formulated "my social environment finds it important…" (α = 0.86; *M* = 2.77, *SD* = 1.42). In parallel, for the items to measure the *descriptive norms of social media users*, we used the introduction "many social media users…" (α = 0.91; *M* = 3.10, *SD* = 1.46); and the items for the *injunctive social media norms*, were introduced by "social media users find it important…" (α = 0.88; *M* = 3.46, *SD* = 1.50).

Intention to discuss the issue. To measure the personal intention to discuss the issue of digital immortality, we introduced the mentioned stem items with "I am planning…" An exemplary item thus is: "I am planning

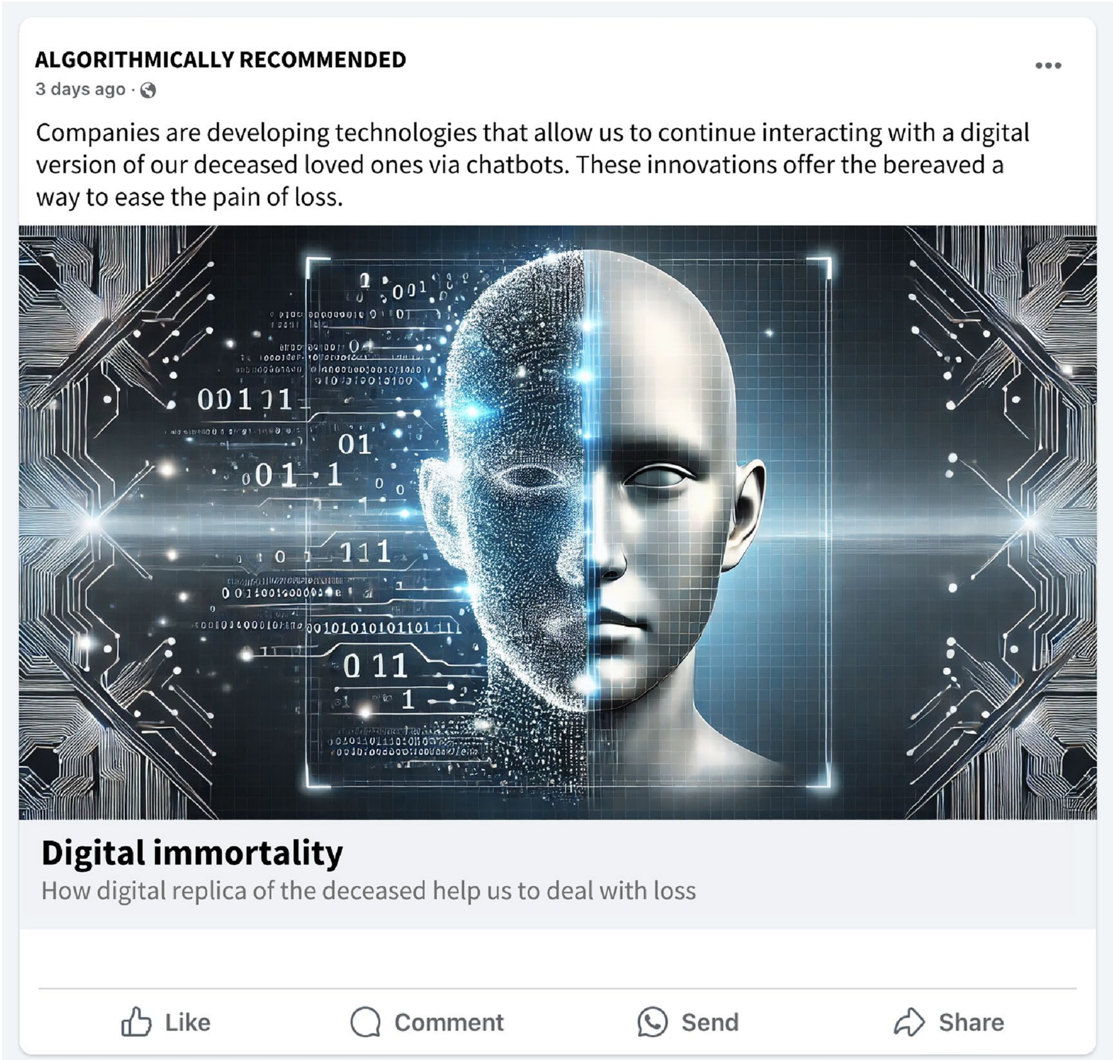

Fig. 2 Exemplary stimulus for the condition algorithmic recommendation

to draw attention on the topic of digital immortality" ($\alpha = 0.88$; $M = 2.28$, $SD = 1.39$).

Perceived social norms of acting on the issue. Perceived social norms of acting on the issue and the intention to act on the issue of digital immortality were measured with a different set of stem items: "… to consider digital immortality for oneself or the loved ones"; "… to provide data for a future digital replica", and "… to sign an initiative to ban digital immortality by law". We combined these items to mean indices. Across all measures, the last item needed to be excluded because of low reliability. Thus, the following measures were only built on two items.

As described above for the discussing norms, the introduction to the items specifies whether they are *descriptive* ($\alpha = 0.88$; $M = 2.14$, $SD = 1.22$) or *injunctive norms* ($\alpha = 0.88$; $M = 2.14$, $SD = 1.24$) *of the social environment* or *descriptive* ($\alpha = 0.87$; $M = 3.00$, $SD = 1.46$) or *injunctive norms* ($\alpha = 0.87$; $M = 2.85$, $SD = 1.46$) *of social media users*.

Intention to act on the topic. We introduced the above-described stem items with "I would…" to measure the intention to act on the issue; an exemplary item thus is: "I would consider digital immortality for myself or my loved ones" ($\alpha = 0.92$; $M = 1.78$, $SD = 1.25$).

Algorithmic appreciation. Participants' algorithmic appreciation was assessed using nine items inspired by Strikovic et al. (2024), covering various aspects of algorithmic appreciation, such as algorithms' perceived ability to save time, aid in discovering new topics, or their help in getting a good impression of the public opinion. As an additional option to the 7-point agreement scale, we provided respondents the category "don't know" ($n = 23$–68). The items were combined to a mean index ($\alpha = 0.69$; $M = 3.35$, $SD = 0.82$), with the "don't know" category treated as missing and index scores calculated only for respondents with valid responses on all items.

Algorithmic awareness (control): Algorithmic awareness was assessed using four items inspired by Strikovic et al. (2024) that evaluate participants' awareness of algorithmic recommendations on social media platforms. The items included evaluations of participants' ability to understand how algorithmic recommendations work, recognize when algorithms are used, and assess why specific recommendations were made. In addition to the 7-point Likert scale, an option allowed participants to indicate "I don't understand the statement" ($n = 18$–28). The items were combined to a mean index, with higher scores reflecting greater algorithmic awareness ($\alpha = 0.82$; $M = 4.72$, $SD = 1.17$). Responses of "I don't understand the statement" were treated as missing, and index scores were computed only for participants with valid responses on all items.

Social media use (control). Participants reported their average daily duration of social media use over the past four weeks, encompassing both private and professional use. Responses were collected via six categories, ranging from 1 = "Less than 1 h" to 6 = "More than 5 h" ($M = 2.28$, $SD = 1.41$).

Attitudes towards digital immortality (control). We asked participants about their attitudes towards the issue of digital immortality, ranging on a 7-point Likert scale from 1 = "very negative" to 7 = "very positive" ($M = 2.21$, $SD = 1.44$).

4.4 Checks

Manipulation check. We included a manipulation check in the survey after the questions on the dependent variables. Participants were instructed to remember the post on digital immortality they have been exposed to and to rate items on the source that recommended the post. Table 1 reports the means across the conditions and items (measured on a 7-point Likert scale) and reveals that, overall, the manipulation worked well. The differences in means are statistically significant and moderate in effect size. Participants recognized when the post was a social, algorithmic, or popularity-based algorithmic recommendation.

Validity check. We also asked participant to which extent they found the scenarios realistic, imaginable, and close to daily life on the 7-point Likert scale. Results show that participants assessments were around the scales' midpoint, meaning that participants did not perceive the described setting as unrealistic ($M = 3.64$, $SD = 1.90$) or not imaginable ($M = 3.79$, $SD = 2.00$). They, however, tended to perceive that the scenarios are not very close to daily life ($M = 3.32$, $SD = 1.78$). There were no differences across the conditions (realistic: $F(3, 1017) = 1.463$, $p = 0.223$; imaginable: $F(3, 1017) = 1.236$, $p = 0.295$; close to daily life: $F(3, 1017) = 1.951$, $p = 0.120$).

4.5 Analysis Strategy

To test the hypotheses, we conducted multivariate analyses of covariance (MANCOVAs), because the dependent variables—perceived descriptive and injunctive norms of both the social environment and social media users—are conceptually related. Specifically, the normative perceptions showed moderate intercorrelations, with Pearson's r ranging from 0.51 to 0.73 for discussion-related norms and from 0.40 to 0.70 for action-related norms.

Specifically, concerning H1, we run a MANCOVA to test whether there are differences across the different types of recommendations (i.e., social, algorithmic, popularity-based algorithmic, or no recommendation) on perceived descriptive and injunctive norms of the social environment and social media users. The MANCOVAs were two-way: in addition to the source of recommendation (the factor of interest), they encompassed the moral evaluation of the issue as a factor (to test whether the effects of the source of recommendation are stable across different moral evaluations of the issue). Furthermore, we included three covariates: social media use, algorithmic awareness, and attitudes toward digital immortality. Gender (X^2 (3, $N = 1021$) = 4.44, $p = 0.218$), age ($F(3,1017) = 0.65$, $p = 0.581$), and education (X^2 (12, $N = 1021$) = 16.80, $p = 0.157$) were equally distributed across

Table 1 Manipluation check

"The post on digital immortality…"	Condition M (SD)				ANOVA		
	Social recommendation	Algorithmic recommendation	Popularity-based algorithmic recommendation	No recommendation	F	p	Eta^2
"… was recommended algorithmically"	2.95 (1.87)	3.90 (2.12)	4.06 (2.26)	3.24 (1.82)	17.03	<.001	.05
"… was recommended algorithmically, because it was most read"	2.77 (1.76)	3.15 (1.80)	4.38 (2.21)	3.16 (1.76)	34.96	<.001	.09
"… was recommended by social contacts"	3.03 (2.17)	2.03 (1.37)	1.97 (1.40)	2.11 (1.36)	24.30	<.001	.07
"… was displayed without recommendation"	3.09 (2.03)	3.54 (2.21)	3.36 (2.11)	3.86 (2.11)	6.04	<.001	.02

the different conditions and therefore not included as covariates into the models. This MANCOVA model was applied to two outcome sets: perceived social norms related to discussing the issue and those related to acting on it.

To test H2, the same MANCOVA models were extended to include an interaction term between algorithmic appreciation and recommendation type, to assess potential moderation effects of algorithmic appreciation. While the MANCOVA approach accounts for the multivariate structure among the dependent variables, it does not provide insights into the direction or consistency of effects across individual variables. Therefore, univariate regression analyses were conducted as follow-up tests to better understand the patterns and directions of associations.

H3 was tested using two regression analyses, one for the intention to discuss the issue and one for taking action. The regression models included the four normative perceptions as independent variables: descriptive and injunctive norms of the social environment and descriptive and injunctive norms of social media users. The analysis was carried out in the software R. For all MANCOVAs, effect sizes are reported as partial eta squared (ηp^2), indicating the proportion of variance in the multivariate outcome uniquely attributable to each effect, controlling for other factors in the model. For regression analyses, unstandardized coefficients (b), standard errors, and adjusted R^2 are reported.

5 Results

The first set of hypotheses (H1, H1a, H1b) proposed that the type of recommendation—social versus algorithmic—would influence perceived social norms of engagement with the issue of digital immortality, in terms of discussing the issue and taking action. The MANCOVA on perceived social norms related to discussing the issue revealed no significant effect of recommendation source (see Table 2). The MANCOVA on perceived social norms related to discussing the issue revealed no multivariate effect of recommendation type (see Table 2), *Pillai's Trace* = 0.007, $F(3, 972) = 0.528$, $p = 0.898$, $\eta p^2 = 0.002$. Likewise, moral evaluation showed no multivariate effect, *Pillai's Trace* = 0.004, $F(1, 972) = 0.915$, $p = 0.454$, $\eta p^2 = 0.001$. This means that participants' normative perceptions—regarding how common and socially approved such discussions are within their social environment and among social media users—were not affected by whether the recommendation was social or algorithmic.

Regarding the covariates, daily social media use (*Pillai's Trace* = 0.028, $F(1, 972) = 6.978$, $p < 0.001$, $\eta p^2 = 0.007$), algorithmic awareness (*Pillai's Trace* = 0.017, $F(1, 972) = 4.306$, $p = 0.002$, $\eta p^2 = 0.004$), and attitudes toward digital immortality (*Pillai's Trace* = 0.089, $F(1, 972) = 23.694$, $p < 0.001$, $\eta p^2 = 0.024$) were significantly associated with perceived discussion norms, with small effects. Follow-up univariate analyses of the individual dependent variables showed that these factors were positively correlated with normative perceptions, indicating that individuals who spent more time on social media, were more aware of algorithms, or held more favorable attitudes toward digital immortality were more likely to perceive discussions as prevalent and socially approved.

Comparably, the MANCOVA on perceived social norms of acting on the issue of digital immortality revealed no significant effects of the recommendation source (Table 3), *Pillai's Trace* = 0.004, $F(3, 972) = 0.308$, $p = 0.988$, $\eta p^2 = 0.001$. Moral evaluation also showed no multivariate effect, *Pillai's Trace* = 0.004, $F(1, 972) = 1.053$, $p = 0.379$, $\eta p^2 = 0.001$. Again, the type of recommendation—whether social, algorithmic, or popularity-based algorithmic—did not influence participants' perceptions of whether their social environment and social media users consider digital immortality for themselves or their loved ones. With respect to covariates, daily social media use (*Pillai's Trace* = 0.054, $F(1, 972) = 13.736$, $p < 0.001$, $\eta p^2 = 0.014$), algorithmic awareness (*Pillai's Trace* = 0.012, $F(1, 972) = 2.938$, $p = 0.020$, $\eta p^2 = 0.003$), and attitudes toward digital immortality (*Pillai's Trace* = 0.300, $F(1, 972) = 104.048$, $p < 0.001$, $\eta p^2 = 0.097$) associated with normative perceptions of acting on the issue. Follow-up

Table 2 MANCOVA for perceived social norms of discussing the issue

	df, *df* error	Pillai	*F*	*P*	ηp²
Recommendation type (i.e., social, algorithmic, popularity-based algorithmic, no)	3, 972	.007	0.528	.898	.002
Moral evaluation of digital immortality (i.e., endorsing, opposing)	1, 972	.004	0.915	.454	.001
Social media use	1, 972	.028	6.978	< .001	.007
Algorithmic awareness	1, 972	.017	4.306	.002	.004
Attitudes towards digital immortality	1, 972	.089	23.694	< .001	.024

Note. DVs = perceived descriptive norm of the social environment, perceived injunctive norm of the social environment, perceived descriptive norm of social media users, perceived injunctive norm of social media users univariate analyses further revealed that both factors were positively correlated with specific normative perceptions. In sum, effect sizes for recommendation type were negligible in both MANCOVAs, providing no support for H1, H1a, and H1b.

The second hypothesis proposed that algorithmic appreciation serves as a moderator when it comes to algorithmic recommendations. To test this, algorithmic appreciation was included as an interaction term in the previously reported MANCOVA models. In both models, we did not find an interaction between the type of recommendation and algorithmic appreciation, neither concerning perceived discussion norms (*Pillai's Trace* = 0.014, $F(3, 847) = 1.000$, $p = 0.446$, $\eta p^2 = 0.004$) nor perceived norms of acting on that issue (*Pillai's Trace* = 0.013, $F(3, 847) = 0.951$, $p = 0.494$, $\eta p^2 = 0.003$). In both cases, effect sizes were negligible, indicating no practically meaningful moderation effects. Thus, hypothesis H2 cannot be confirmed.

The third set of hypotheses (i.e., H3, H3a) proposed that perceived social norms would predict individuals' intention to engage with the issue of digital immortality—specifically, the intention to discuss the topic and to take action—while stronger effects were expected for norms of the immediate social environment compared to those of social media users. regression analyses supported this assumption (Tables 4, 5). For discussion intentions (Table 4), descriptive and injunctive norms of the social environment were positively associated with intentions ($b = 0.237$ and 0.248, respectively, both $p < 0.001$), whereas descriptive norms of social media users were not significant ($b = 0.045$, $p = 0.164$); injunctive norms of social media users showed a small but significant association ($b = 0.156$, $p < 0.001$). Including the

Table 3 MANCOVA for perceived social norms of acting on the issue

	df, df error	Pillai	*F*	*P*	ηp^2
Recommendation type (i.e., social, algorithmic, popularity-based algorithmic, no)	3, 972	.004	0.308	.988	.001
Moral evaluation of digital immortality (i.e., endorsing, opposing)	1, 972	.004	1.053	.379	.001
Social media use	1, 972	.054	13.736	< .001	.014
Algorithmic awareness	1, 972	.012	2.938	.020	.003
Attitudes towards digital immortality	1, 972	.300	104.048	< .001	.097

Note. DVs = perceived descriptive norm of the social environment, perceived injunctive norm of the social environment, perceived descriptive norm of social media users, perceived injunctive norm of social media users

Table 4 Regressions of perceived social norms on discussing the issue

	b	SE	*t*	*P*
Perceived descriptive norm of social environment	.237	.04	6.357	< .001
Perceived injunctive norm of social environment	.248	.04	6.850	< .001
Perceived descriptive norm of social media users	.045	.03	1.391	.164
Perceived injunctive norm of social media users	.156	.03	4.998	< .001
Social media use	.072	.02	2.969	.003
Algorithmic awareness	.029	.03	1.004	.315
Attitudes towards digital immortality	.131	.03	5.258	< .001

Note. Adjusted *R*-squared: .447

Table 5 Regressions of perceived social norms on acting on the issue

	b	SE	*T*	*p*
Perceived descriptive norm of social environment	.227	.03	6.814	< .001
Perceived injunctive norm of social environment	.215	.03	6.418	< .001
Perceived descriptive norm of social media users	.047	.02	1.902	.057
Perceived injunctive norm of social media users	.039	.03	1.555	.120
Social media use	.028	.02	1.424	.154
Algorithmic awareness	−.015	.02	-0.635	.526
Attitudes towards digital immortality	.332	.02	14.335	< .001

Note. Adjusted *R*-squared: .550

control variables, the model explained substantial variance (adjusted $R^2 = 0.447$). For action intentions (Table 5), both descriptive and injunctive norms of the social environment predicted intentions ($b = 0.227$ and 0.215, respectively, both $p < 0.001$), whereas norms attributed to social media users were not significant (descriptive: $p = 0.057$; injunctive: $p = 0.120$). Attitudes toward digital immortality showed a strong positive association with action intentions ($b = 0.332$, $p < 0.001$). The model explained substantial variance (adjusted $R^2 = 0.550$; including the control variables). Together, these findings support H3 and H3a.

6 Discussion

This study aimed to investigate how different types of social media recommendations—social, algorithmic, and popularity-based algorithmic—affect normative perceptions and, ultimately, individuals' intentions to engage with a moral issue. The central theoretical contribution lies in the combination of theories on influential technology in human–machine communication (Nass and Moon 2000; Sundar 2008), human-AI interaction (Shin 2024, 2025), and social norms research (Cialdini et al. 1990; Rimal and Real 2005). Empirically, the study provides an experimental comparison of social and algorithmic recommendation types and a test of their effects on normative perceptions of issue engagement, an area that has not been systematically explored thus far (Huang and Wang 2023).

The study's main result is that algorithmic and social recommendations did not affect perceived descriptive or injunctive norms (Hypotheses 1 and 2 therefore were not supported). At the same time, perceived norms—those linked to participants' immediate social environment—were associated with engagement intentions (H3). Thus, the study finds support for the behavioral relevance of norm perceptions, but not for the idea that recommendations shape those perceptions.

The absence of differences between social and algorithmic recommendations in shaping perceived social norms is consistent with the broader literature. Meta-analytic evidence indicates no systematic advantage of either human or algorithmic sources across outcomes (Huang and Wang 2023). The present study shows that, for issue-specific normative perceptions, recommendation labels may not be sufficient to generate differences in a single-exposure setting. As such, the experimental design can be regarded as a conservative test of algorithmic and social influence, because real-world recommendation environments involve repeated exposures and multiple signals (e.g., social feedback, behavioral reinforcement). More broadly, the findings indicate that normative influence via social and algorithmic recommendations is conditional rather than automatic. The design of the present study points to four possible boundary conditions that may make normative effects more likely to emerge.

First, norm perceptions may require repetition before they shift. This aligns with social learning theory (Bandura 1986) and cultivation theory (Gerbner and Gross 1976), which emphasize that normative beliefs develop through repeated and socially reinforced exposure over time. Thus, a one-time, passive exposure to a recommendation as in the present study setting might not be sufficient to influence normative perceptions as it may not adequately capture the process by which normative perceptions typically evolve on social media (Geber and Hefner 2019).

Second, susceptibility to recommendation cues likely varies. While we considered algorithmic appreciation as an important moderator, there might be other traits that are relevant. Reactance theory (Brehm 1966), for instance, suggests that some individuals resist perceived communicative influence. This implies that reactance may moderate the influence of both social and algorithmic recommendations, thereby diluting overall effects.

Third, the issue itself may matter. Digital immortality may not be polarizing enough to activate normative differences. Although the topic is novel and not yet normatively loaded, individuals may have been too unfamiliar with it and therefore unable to form meaningful normative beliefs in response to the stimulus, reducing variance. The generally low means across all issue-related constructs suggest a negative evaluation and low familiarity with that issue, potentially generating a general rejection of the issue.

Fourth, recommendation labels may not function as "norm cues" unless users treat them as epistemically meaningful. Recent work argues that people interpret what algorithmic curation implies about credibility, legitimacy, and social relevance (Shin 2024, 2025). From this perspective, "recommended" or "most read" may not be automatically processed as socially meaningful. Participants may instead treat the label as too weak evidence to override their sense of what counts as a socially meaningful signal.

Finally, the study provides evidence that normative perceptions—especially of one's immediate social environment—are positively associated with intentions to engage with the issue, including both discussing and acting upon it. This finding is consistent with prior work on normative influences (Cialdini et al. 1990; Rimal and Real 2005), which emphasizes the behavioral importance of social norms in general (Manning 2009) and the stronger behavioral impact of proximal reference groups compared to more abstract collectives (Patrick et al. 2012; Mollborn et al. 2014), such as social media users. This finding shwos the potential of normative perceptions as a central mechanism in influence processes, warranting more focused attention in future research on algorithmic recommendation. This is especially pertinent in the context of algorithms based on collaborative filtering, which may incorporate explicit popularity cues—such as "most read" indicators—thereby increasing the likelihood of normative influence (Zarouali et al. 2022).

6.1 Theoretical implications

The combination of theories on influential technology in human–machine communication (Nass and Moon 2000; Sundar 2008), human-AI interaction (Shin 2024, 2025), and social norms research (Cialdini et al. 1990; Rimal and Real 2005) offers a promising framework for future inquiry into the normative influences of algorithmic recommendations and, beyond, AI-driven content curation. However, this framework should more explicitly incorporate the temporal dimension of normative perception formation, particularly given the dynamic and iterative nature of social media environments. Normative beliefs shaped by both social and algorithmic recommendations are unlikely to emerge from isolated exposures; instead, they develop through repeated and consistent exposure to cues over time. Moreover, theoretical approaches should emphasize users as active sensemakers who calibrate trust dynamically, rather than as passive recipients of algorithmic recommendations (Shin 2025).

Recognizing the temporal aspect also allows for an understanding of the broader implications of AI-mediated content on the formation of norms and values within society. While our findings did not reveal immediate effects of algorithmic recommendations on issue-related normative perceptions, they do not preclude cumulative effects. In fact, the long-term, aggregated influence of minimal shifts in individual-level perceptions may contribute to the establishment or reinforcement of collective norms at the societal level (Geber and Sedlander 2022). Thus, even in the absence of short-term effects, the normative role of AI-driven curation warrants sustained scholarly attention—particularly regarding its potential influence on public discourse and social norms.

6.2 Limitations and outlook

The study design has limitations that point to directions for future work. First, the thematic context of digital immortality, while novel and theoretically rich, may have been too unfamiliar to allow for some participants to form stable normative judgments after a single exposure. Although novelty can be advantageous when norms are still developing (Galvão et al. 2021), the low mean scores across key measures indicate limited engagement with the issue in this sample. Future replications might therefore test more recognizable or divisive issues topics (e.g., AI surveillance, algorithmic hiring). Second, our manipulation operationalized recommendation types via explicit recommendation labels. This approach was chosen to isolate cue-based effects consistent with CASA (Nass and Moon 2000) and MAIN (Sundar 2008), but it does not fully capture how recommendation cues are experienced on social media. On social media, they are embedded in more complex interfaces and reinforced through repeated encounters as well as algorithmic and social feedback. Accordingly, future studies should increase ecological validity through interactive simulations and incorporate behavioral outcomes (e.g., clicks, likes, shares) alongside self-reports. Third, algorithmic appreciation was treated as a unidimensional moderator in this study; emerging work, however, conceptualizes appreciation of and trust in algorithms as a multidimensional process involving distinct evaluative layers (Shin 2025)—such as functional confidence and epistemic endorsement. This should be considered in future research. Fourth, measuring attitudes toward digital immortality prior to the experimental exposure may have primed participants, potentially influencing how they subsequently reported their own or their social environment's views on this novel topic. We included baseline attitudes to account for pre-existing evaluations, but future research could omit baseline measures, counterbalance measurement order, or include a control group without pre-measures to assess potential priming effects more directly.

6.3 Conclusion

This study aimed to investigate how different types of recommendations—social, algorithmic, and popularity-based algorithmic—affect users' normative perceptions and their intentions to engage with a novel moral issue (i.e., digital immortality). The findings provide no evidence that recommendation label itself alters normative perceptions, underscoring that recommendation systems do not deterministically produce normative influence. Their normative effects may emerge more gradually through repeated encounters. At the same time, the findings demonstrate that perceived norms are a predictor of individuals' willingness to discuss and act on the issue. This highlights that normative perceptions are critical drivers of moral engagement and therefore need to be considered in future studies on the implications of AI-based content curation. Future research could examine whether the null effects of algorithmic recommendations on normative perceptions hold for more familiar or polarized issues than digital immortality and in more naturalistic settings. Ultimately, understanding how AI-driven recommendation systems interact with normative processes remains essential for evaluating their broader societal impact.

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Declarations

Conflict of interest The authors declare no competing interests.

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