Explanations for Recommended Low-Interest News Articles Fail to Persuade Selective News Avoiders

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Abstract

Selective exposure, the phenomenon of mainly selecting content that aligns with existing preferences, and the related issue of selective news avoidance can limit engagement with diverse news content in news recommender systems. To address this problem, we designed a set of explanation strategies for news articles on low-interest topics, targeting key drivers of selective news avoidance: distrust in news and perceived bias, information overload, perceived news negativity, and perceived irrelevance. After a pre-study to identify suitable phrasings, we conducted two mixed-design online experiments ($N_1 = 150$, $N_2 = 200$) using personalized news recommendation interfaces. Across both hard and soft news categories, we examined whether these needs-based explanation strategies affected the selection and perception of recommended low-interest articles, and evaluated the explanations across conditions. While the explanations did not significantly increase selection overall, those addressing perceived irrelevance were descriptively associated with higher low-interest article selection rates than the other strategies. In addition, higher perceived explanation salience was significantly associated with both a higher likelihood of selecting low-interest articles and a higher reported likelihood of reading them in full. The explanations also shaped how the news recommendations were perceived, particularly with regard to trustworthiness and understandability. Overall, the findings suggest that the impact of textual explanation strategies in news recommenders may depend not only on their content, but also on their salience and interface integration.

Keywords

selective news avoidance, news recommender systems, explanations, news engagement

1. Introduction

Recommender systems play an increasingly central role in how people encounter news online [1, 2], acting as mediators between available content and what news users actually consume [3]. In doing so, they shape both the provision and presentation of content, influencing which news users select and how they engage with them [2, 4].

While news recommender systems can help users navigate large amounts of content and access news that matches their interests, they can also narrow users' exposure to other news by reinforcing existing preferences and information diets [5, 6]. This dynamic is closely related to selective exposure, which involves individuals seeking information that is perceived as preferred or relevant to them, while ignoring other sources [7, 3]. In practice, recommender systems often optimize more for engagement than for broader exposure to diverse content [8, 9], which can further strengthen this pattern. In such settings, items that are more distant from users' established interests are less likely to be selected. One important manifestation of this dynamic in the news domain is *selective* news avoidance, which describes the disengagement from specific types of news content [10]. The topics avoided in this way may vary considerably across users [11]. For example, categories such as political news or sports may receive far less attention from some users than from others.

As a result, selective news avoidance can have serious societal consequences, including lower democratic participation. Compared with *news seekers*, *news avoiders* are less politically mobilized, which can in turn affect electoral behavior [12]. At the same time, people's motivations for reading news—and

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thus also their reasons for avoiding it—differ [13, 14]. Common drivers of news avoidance include distrust in news [15, 16, 17], information overload, perceived irrelevance, and perceived news negativity [18]. As news avoidance is increasing globally [14], especially among young audiences [19, 13, 20], there is a growing need for interventions that encourage engagement with a broader range of news content.

In this paper, we focus on the persuasive role of news recommender interfaces (cf. [21]), particularly in shaping *how* information is presented rather than only *what* is recommended. One promising mechanism at this interface level is the use of explanations. In recommender systems, explanations have been shown to increase perceived trust and transparency (cf. [22]), but they can also steer users' choices and consumption behavior [23, 24, 25]. In the context of news recommenders, explanations have received some attention in prior research, though much of the existing work focuses on generating or modeling explanations, while fewer studies have examined how such explanations affect users [26, 27, 28].

Against this background, we introduce five strategies for news recommender explanations, which we refer to as *needs-based explanations*. We conceptualize needs-based explanations as an extension of conventional recommender explanations: rather than primarily justifying why an item is recommended, they adopt a barrier-oriented framing that addresses the motivational and psychological barriers that may lead users to avoid certain news content. This concept is grounded in Uses and Gratifications Theory [29] and informed by prior work on techniques for addressing such barriers.

Despite this potential, little is known about whether explanations can be used not only to clarify recommendations, but also to encourage engagement with news topics that users would otherwise be inclined to avoid. While explanations are increasingly used to support transparency and trust [30, 31], their potential to mitigate selective news avoidance remains underexplored [32, 28, 33]. This reveals a gap in news recommender research, particularly with regard to interface interventions that address the drivers of selective news avoidance directly.

To address this gap, we first conducted a pre-study to identify suitable phrasings for five needs-based explanation strategies. These were then evaluated in two online user studies with US-based participants ($N_1 = 150$, $N_2 = 200$), in which they interacted with personalized news recommender interfaces. Across both hard and soft news categories, we examined whether needs-based explanations affect the selection of low-interest news articles as well as perceptions of the recommended articles and evaluations of the explanations.

This paper makes three main contributions. First, it introduces the concept of needs-based explanations as a way of addressing selective news avoidance in news recommender interfaces. Second, it provides empirical evidence from a pre-study and two user studies on whether such explanations can encourage the selection of low-interest news articles. Third, it offers insights into how explanation design may need to account not only for explanation content, but also for factors such as salience and news topic.

We address the following research questions:

RQ1: To what extent do needs-based explanations affect readers' selection of low-interest news articles, and is this effect moderated by age or other demographic characteristics?

RQ2: To what extent do needs-based explanations affect readers' perceptions of the recommended news articles, and how do readers evaluate different explanation strategies?

2. Background

This section positions the paper in relation to prior work at the intersection of news recommender systems, selective news avoidance and explainable recommender systems. Together, these strands of research provide the foundation for the concept of needs-based explanations and for the research gap addressed in this paper.

2.1. News Recommender Systems and Diversity of Exposure

News recommenders can help users navigate today's high-choice news media environment by personalizing both the content they see and its order to match their preferences [32, 4], influencing what news readers are exposed to and likely to engage with [3]. This role is particularly important in the news domain, where the selection of and diversity in exposure to content have direct societal consequences [2]. Because news is often time-sensitive, many news items receive public attention only for a limited period. News recommendations therefore need to account for factors such as information quality, public relevance, and diversity of perspectives and topics [2]. At the same time, many news recommender systems optimize for click-through rates, relevance, and engagement, which can lead them to prioritize familiar or broadly preferred content over societally important content that may not align with users' existing preferences [34].

News recommender systems research has largely focused on improving recommendation quality through personalization, relevance, and engagement optimization [4, 35]. Comparatively less attention has been directed toward interface-level interventions that shape how recommendations are presented and how users engage with them, particularly in ways that could address selective news avoidance [36]. At the same time, recent work has begun to explore such interface design aspects more directly, for example through normatively motivated recommendation designs [1] and interface nudges such as positioning and visual highlighting [6, 33]. Still, this line of research remains relatively limited, which highlights the need to examine recommendation design not only in terms of algorithmic performance, but also as a means of broadening users' news exposure.

2.2. Selective News Avoidance

News avoidance has become an increasingly prevalent phenomenon in online news environments. According to the 2025 Reuters Institute Digital News Report, around 40% of respondents from 48 countries indicated that they avoid the news sometimes or often, compared to 29% in 2017 [14]. This development has direct societal consequences, affecting not only the news industry [37], but also democratic participation [12].

Skovsgaard and Andersen [18] distinguish between intentional and unintentional forms of news avoidance. Unintentional avoidance refers to a more subconscious preference for consuming other types of information over news, whereas intentional avoidance describes the active choice to disengage from news—often in relation to specific news topics. This topic-specific form is commonly discussed as selective news avoidance [10]. Andersen et al. [38] further describe selective news avoidance as comprising both a stable, *trait* dimension and a more temporary, *state* dimension, each affecting news consumption differently. In this paper, selective news avoidance is primarily operationalized in terms of the trait-like tendency to avoid certain news topics.

The reasons for selectively avoiding news are closely tied to users' motivations and needs [13]. Among the main drivers are (1) distrust in news and perceived bias in reporting [16, 17], (2) information overload—the feeling of being confronted with too much information at once [39], (3) a perceived lack of personal relevance, and (4) the perceived negativity of news, which may affect users' mood or emotional well-being [18, 11, 40, 41].

2.3. Approaches to Addressing Drivers of News Avoidance

Although the drivers of news avoidance have received considerable scholarly attention, less attention has been paid to interventions that directly address them [10]. Still, several article-level approaches suggest possible ways of addressing specific drivers of news avoidance.

Regarding distrust in news, prior work suggests that communicating a fact-checking process [42, 43] and presenting multiple perspectives in a more balanced format [15] can improve trust in news content. These approaches are especially relevant because bias is one of the main reasons why people distrust the news [17, 16]. Addressing news overload, Park [44] describes how news efficacy—the confidence

to navigate and understand news—is connected to reduced cognitive load, which may in turn help mitigate news avoidance [45].

To address perceived irrelevance, social influence techniques such as social proof—the tendency to infer the legitimacy or appropriateness of a behavior based on how others commonly do it [46]—have been explored as potential interventions. Social popularity cues and related forms of social proof have been shown to increase engagement with news content, particularly among younger audiences [47, 48, 49, 50, 51, 52]. Finally, to counter perceived news negativity, constructive journalism—which adopts a more positive and solution-oriented perspective in reporting—has demonstrated promising effects [53, 54].

2.4. Explanations in News Recommender Systems

In recommender systems, explanations are commonly studied with a focus on clarifying why an item is recommended [55]. In the context of news recommenders, however, explanation research remains comparatively limited, particularly with regard to approaches that address the drivers of selective news avoidance.

Some studies have examined interface-level cues that may influence engagement with news recommendations. Yang [50], for example, found that popularity-themed headlines had a stronger effect on article selection than regular topical headlines. Experiments testing social influence cues for news articles have produced mixed results: while Kulkarni and Chi [56] found social annotations to be persuasive, Agapie and Munson [57] reported negative effects on reading interest for some conditions. Both studies suggested further research in this direction to better understand effects of these kinds of annotations. More recently, social popularity labels for news articles have been shown to increase news engagement [48]. Taken together, these studies suggest that article-level cues can influence users' news choices, but that their effects depend on how such cues are designed and presented.

Taken together, existing work suggests that explanations and related article-level cues can influence news engagement, but little is known about whether explanations can be systematically designed to address the different motivations underlying selective news avoidance. This paper addresses that gap through the introduced concept of needs-based explanations.

3. Methods

The research consisted of three stages: (1) a *Pre-Study* to identify the most effective phrasing for different variations of needs-based explanations, (2) an initial user study testing these best rated explanations (*Study 1* with $N_1 = 150$), and (3) a follow-up study with an adjusted visual explanation presentation (*Study 2* with $N_2 = 200$). The two main studies employed similar experimental designs, allowing to examine the findings' robustness across variations in the presentation of the needs-based explanations.

3.1. Procedure

Data collection for each main study was completed within one day. Study 1 and Study 2 were conducted two weeks apart. The study procedure is depicted in Figure 1. Both studies consisted of two parts:

Demographics and Pre-Questionnaire After giving informed consent to participating in the study and answering a demographics survey (gender, age, location, education), participants completed a pre-questionnaire. This pre-questionnaire included questions on news consumption frequency, main news platform, news avoidance frequency and main reasons for avoiding the news. In addition, participants were asked to select their favorite and least favorite news category from one list with hard news categories and one with soft news categories, followed by two ratings on the extent to which they either enjoy or avoid reading news from their selected categories.

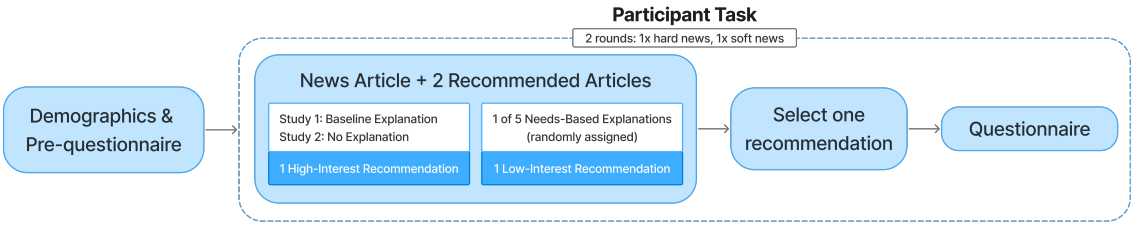

Figure 1: Study Flow Diagram for both main studies (Part 1: Demographics & Pre-questionnaire; Part 2 (two rounds): Selection of one recommended article followed by a questionnaire)

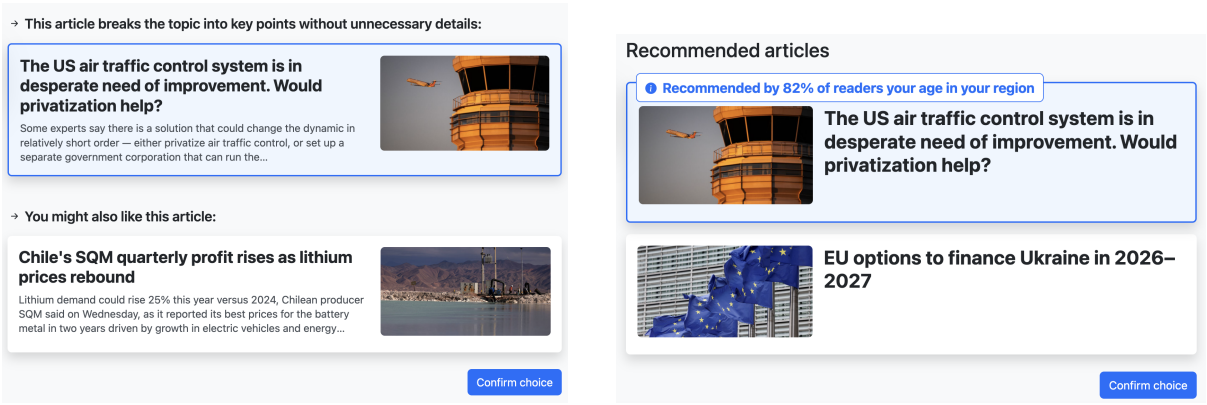

Figure 2: Example of the interactive part in Study 1 (left) and Study 2 (right), showing the different presentation of explanations across the two studies

Participant Task This part included two interactive rounds, showing an online news article with two recommended news article previews (see Figure 2). Each round only showed articles of one news type (hard news or soft news, presented in a randomized order). The recommendations were personalized based on participants' self-reported topic preferences: one of the two recommended articles stemmed from their favorite news category, while the other was from their least favorite category (presented in randomized order). As a result, news categories appeared at varying frequencies across participants, reflecting the personalized character of the study design.

The low-interest article recommendations were shown with one of the needs-based explanations identified in the Pre-Study (see Table 1). In Study 1, both recommended articles were accompanied by an explanation: the high-interest recommendation displayed the generic label "You might also like this article," which also served as a baseline explanation for the low-interest recommendation. In Study 2, neither the high-interest recommendation nor the baseline condition of the low-interest recommendation included an explanation. Participants were asked to select their preferred recommended article, followed by a questionnaire about the recommendations and depicted explanation(s).

3.2. Research Design

In both Study 1 and Study 2, we conducted an online user experiment in a personalized recommendation setting to investigate whether needs-based explanations influence users' selection of low-interest news articles compared to high-interest news articles. The presented news articles and the explanations for low-interest recommendations were subject to a single-arm 2 (hard or soft news) x 5 (needs-based explanation strategy) mixed research design with repeated measures, as each participant completed two news article recommendation scenarios, featuring two different explanation strategies for the low-interest item. Restricting each scenario to two options enabled a direct comparison between a high-

interest and low-interest article, making article choice easier to interpret regarding explanation effects. The explanation shown alongside the low-interest article was randomly assigned across participants and rounds.

In Study 1, six explanation conditions were tested for the low-interest article: five needs-based explanations (see Table 1) and the baseline condition "You might also like this article." The high-interest recommendation consistently displayed the baseline explanation. In Study 2, the high-interest recommendation was shown without an explanation, and the low-interest article additionally included a no-explanation baseline condition.

3.3. Participants

We recruited participants via Prolific for the Pre-Study and both main studies. Participants lived in the US, were fluent in English, and only participated in one of the studies. The Pre-Study verified participant authenticity and attention through one instructional manipulation check, while the main studies included two attention checks each.

The Pre-Study included 25 participants who answered the questionnaire and were remunerated with £17.94/hr.

For Study 1, we recruited 150 adults (55.3% male, 43.3% female, 1.3% non-binary), divided into two age groups (18-35, 36-100) with $n = 75$ each. Participants received an average compensation of £10.50/hr for completing the study. Respondents' ages ranged from 20-80 ($M = 40.07$).

In Study 2, we recruited 200 adults (n=100 for age groups 18-35 and 36-100 each). Participants received an average compensation of £10.60/hr for completing the study. Respondents' ages ranged from 19-74 ($M = 39.70$). 41.5% identified as female, 56% as male, 2% as non-binary, and 0.5% preferred not to say.

3.4. Materials

Prototype code and data for both studies are available at: Study 1[1], Study 2[2]

3.4.1. News article dataset

We selected news articles from a dataset of $\approx 25,800$ entries, which had been collected in November 2025 through the Web and News Search API Newscatcher. The dataset included news articles from nine prominent online news sources in the US and UK, pre-categorized into 13 news categories.

After removing unsuitable entries (e.g., articles with missing images, duplicates, podcast transcriptions) and UK-specific entries, we adjusted the remaining articles and their assigned categories to best suit the study design and to create a usable dataset that includes the most common news categories. The result of these modifications was a set of entries from 12 different news categories, where six categories were attributed to hard news (*Business & Economics, International News, Crime, Finance, Politics, Public Health & Health Policy*), and another six to soft news (*Lifestyle, Entertainment, Science, Tech, Sports, Personal Health & Wellbeing*).

3.4.2. Explanations

To address the different main reasons for (selective) news avoidance, we created needs-based explanations directed at each of the following avoidance factors:

1. *DIS*: Distrust in news
2. *IRR*: Perceived irrelevance of news
3. *INF*: Information overload
4. *NEG*: Perceived negativity of news

We also added a fifth explanation as a popularity baseline (*POP*).

[1] https://anonymous.4open.science/r/needs-based-explanations-study-1
[2] https://anonymous.4open.science/r/needs-based-explanations-study-2

Table 1
Pre-Study: Highest rated explanation for each addressed news avoidance factor. M_{clear} and SD_{clear} refer to perceived clarity; M_{click} and SD_{click} indicate the likelihood of selecting the related recommended article

Type	Needs-based explanation	M_{clear}	SD_{clear}	M_{click}	SD_{click}
DIS	The information in this article has been fact-checked for accuracy	4.40	0.96	4.04	1.14
IRR	This article is recommended by 82% of readers your age in your region	3.96	1.24	3.44	1.23
INF	This article breaks the topic into key points without unnecessary details	4.28	0.84	3.64	1.19
NEG	This article focuses on solutions and constructive ways forward	4.24	0.72	3.68	1.18
POP	This article is trending right now	4.32	1.11	3.40	1.44

Pre-Study Based on related theory and previous research (see Chapter 2.3), we developed four to five explanation variants for each addressed avoidance factor (as well as for the *POP* explanation). To identify the most suitable phrasing for each explanation, we conducted a Pre-Study in which participants rated the different variants on 5-point Likert scales in (a) whether the explanation is clear and easy to understand, and in (b) likelihood of checking out the recommended article.

The highest rated explanations (in a slightly shortened version in Study 2) were selected for the main studies (see Table 1). Addressing distrust in news, the first explanation includes verification cues and mentioning of multiple perspectives. For the factor of perceived irrelevance, we employed social influence theory [58] for the explanation strategy, and Cognitive Load Theory [59] as well as the concept of news efficacy [44] to address information overload. On the factor of perceived news negativity, we included the concept of constructive journalism [54, 53] in the explanation strategy.

3.5. Measures

In addition to collecting demographic information and responses from the pre-questionnaire, we evaluated participants' behavior and assessments in the interactive part by using a combination of behavioral choice and self-reported 5-point Likert-scale measurements.

Article selection The primary dependent variable was whether a participant selected the low-interest article recommendation, coded as a binary variable. In both rounds, participants had to choose between the high-interest and low-interest article recommendations.

Likelihood to read in full For both recommended articles, participants reported the likelihood that they would read the article in full on a 5-point Likert scale.

Article perceptions Participants evaluated the recommended articles in five different 5-point Likert-scale statements: (1) The article fits my preferences. (2) The article seems constructive. (3) The article seems easy to understand. (4) The article seems trustworthy. (5) The article seems relevant. In Study 1, statement (1) was evaluated for both recommendations, and statements (2)-(5) were shown only for the low-interest article. In Study 2, participants evaluated both recommended articles on all statements.

Explanation perceptions To assess participants' impressions of the needs-based explanations, we measured these in five statements on a 5-point Likert scale:

1. The explanation is easy to understand.
2. The explanation is useful.
3. The explanation influenced my choice.
4. The explanation grabbed my attention.
5. I would like to see more explanations like this for recommended news articles.

4. Results

4.1. News consumption habits

Participants reported their news consumption habits in both studies. Regarding news consumption frequency, the majority of participants reported looking at online news at least daily (both studies: 74%). Only 0-2% of participants reported to never consume online news, suggesting the proportion of extensive news avoiders was low.

Regarding the most frequently used platform for news consumption, Social Media was selected most (both studies: 46%), followed by news websites (Study 1: 31%, Study 2: 26%) and news aggregators (Study 1: 11%, Study 2: 16%). When filtering for age groups (Group A: age 18-35 and Group B: age >35), there were significant differences: Social Media were more popular among younger participants (Group A: 59-61%, Group B: 31-34%), than news websites (Group A: 20-21%, Group B: 32-41%). This is consistent with prior research on young audience's news preferences [14].

When it comes to news topic preferences, Sports is the most selected both favorite and least favorite soft news category across both studies (Most favorite: 21-22%, Least favorite: 34-35%). Among hard news categories, Politics is most popular (Study 1: 41%, Study 2: 33%), but also one of the most selected least favorite categories (Study 1: 29%, Study 2: 22%), together with Crime (24-25%) and Finance news (19-23%). The selected favorite news categories received a high enjoyment rating in both Study 1 and Study 2 (Hard news: $M = 5.96 - 6.01, SD = 1.14 - 1.20$; Soft news: $M = 6.25 - 6.40, SD = 0.83 - 1.02$), while the selected least favorite categories were reported with a high avoidance rating (Hard news: $M = 4.84 - 4.85, SD = 1.76 - 1.83$; Soft news: $M = 5.15 - 5.23, SD = 1.81 - 1.83$).

Regarding their personal news avoidance behavior, the majority of participants reported an occasional (46-51%) or regular news avoidance (23-32%), as well as a selective news avoidance (16-18%). As main reasons for their news avoidance, the perceived negativity of news was selected most (Study 1: 56%, Study 2: 65%), followed by perceived irrelevance (Study 1: 45%, Study 2: 38.5%) and information overload (Study 1: 33%, Study 2: 38.5%). Distrust in news was selected least (Study 1: 23%, Study 2: 25.5%). The ratings were relatively similar across both age groups, with the exception that in Study 2, significantly more participants from Group A than Group B selected information overload (48% vs. 29%). Regarding distrust in news, contrasting results were found: In Study 1, this factor was selected more often in Group A (27% vs. 19%), whereas in Study 2, this option was chosen more often by Group B (31% vs. 21%).

4.2. Article Selection and Likelihood to Read Article in Full

Overall low-interest article selection increased from Study 1 to Study 2 (22.3% → 28.8%). Furthermore, in both studies, the first interaction round showed a higher selection rate than the second round (Study 1: 24% → 21%, Study 2: 33% → 24.5%), although this difference was not significant (Study 1: $p = 0.49$, Study 2: $p = 0.09$).

In addition to selection behavior, participants' perceived likelihood of reading the full article (*LRF*) differed significantly between low- and high-interest articles ($M_{low} = 2.75, SD_{low} = 1.48$, $M_{high} = 3.48, SD_{high} = 1.27, p < 0.01$), with similar ratings for low-interest articles both with and without an explanation present ($M = 2.75 - 2.76, SD = 1.36 - 1.51$).

Explanation Type The selection rate differs between explanation types (see Table 3): Low-interest articles with explanation type IRR (Study 1: 28.6%, Study 2: 34.4%) were chosen more often than when presented with any other or no explanation. However, there was no significant effect of explanation type on the probability of selecting the low-interest news article compared to the baseline condition (e.g., Study 2: all p > 0.48).

News Type and Category We further explored whether the effect of explanations on article selection differed by news type. Across both studies, the needs-based explanations appeared to be descriptively

Table 2
Low-interest article selection rates and likeliness to read article in full (LRF) ratings per news category

News Category	Type	Selection	M_{LRF}	SD_{LRF}	n
Public Health	hard	56.5%	3.52	1.34	23
Business	hard	47.6%	3.24	1.30	21
Politics	hard	43.9%	3.05	1.38	41
International	hard	38.9%	3.17	1.38	18
Lifestyle	soft	32.7%	2.63	1.33	49
Crime	hard	28.6%	3.42	1.37	49
Science	soft	26.3%	3.32	1.49	19
Personal Health	soft	22.2%	2.22	2.22	9
Tech	soft	22.2%	2.22	1.28	27
Entertainment	soft	20.0%	3.03	3.03	30
Sports	soft	15.9%	1.74	1.22	69
Finance	hard	15.6%	2.58	1.59	45

more beneficial for soft than for hard news, though the pattern differed between studies. In Study 1, low-interest soft-news articles were not selected with the baseline explanation (0%), compared to a rate of 16.2% when accompanied by a needs-based explanation. For hard news, selection rates were 37.0% in the baseline condtion and 29.0% with needs-based explanations. In Study 2, we also observed a stronger increase in low-interest article selection with needs-based explanations for soft news (16.7% → 23.7%) than for hard news (34.2% → 35.2%), although overall selection rates were higher for hard news (see Table 2). However, a mixed-effects logistic regression with news type (soft news vs. hard news), needs-based explanation presence, and their interaction as predictors revealed that neither the effect of news type (p = 0.11), of needs-based explanation presence (p = 0.91), nor of their interaction (p = 0.54) reached statistical significance.

The perceived likelihood of reading the full article differed significantly across low-interest news categories ($F(11, 388) = 6.64$, $p < .001$). Post-hoc Tukey HSD pairwise comparisons indicated that particularly articles from the *Sports* category were consistently associated with lower LRF ratings compared to multiple other topics including *Crime*, *Business & Economics*, *Entertainment*, *International News*, *Lifestyle*, *Politics*, *Sports* and *Public Health & Health Policy* (all $p < 0.05$), which suggests that the effectiveness of explanations may vary depending on the specific news category.

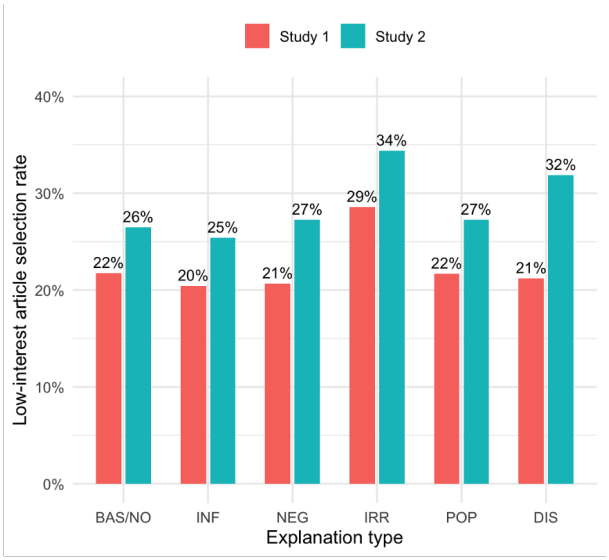

Figure 3: Low-interest article selection per explanation condition

Age and Gender When comparing age groups, respondents older than 35 selected low-interest articles at slightly higher rates than the 18-35 group (Study 1: 21.3% vs. 23.3%, Study 2: 27.9% vs. 29.6%). Regarding gender, male participants selected low-interest articles more often than female participants (Study 1: 24.7% vs. 20.0%, Study 2: 30.8% vs. 25.3%). However, no significant differences in low-interest article selection were observed between genders in either Study 1 ($\beta = 0.27, SE = 0.29, p = 0.34$) or Study 2 ($\beta = 0.27, SE = 0.23, p = 0.23$).

Table 3
Perception ratings for recommended articles (Study 2): Overall higher ratings for high-interest recommendation; stronger low-interest article ratings with explanations (M_{expl} (SD_{expl})) than without (M_{noexpl} (SD_{noexpl})) in trustworthiness and understandability vs. lower ratings in constructiveness and relevance

	Low-interest				High-interest	
Measure	M_{expl}	SD_{expl}	M_{noexpl}	SD_{noexpl}	M	SD
Constructiveness	3.37	0.99	3.55	0.88	3.72	0.90
Relevance	3.16	1.16	3.27	1.10	3.68	1.04
Trustworthiness	3.63	0.89	3.60	0.74	3.77	0.85
Understandability	3.70	0.97	3.67	0.86	3.95	0.82

4.3. Article Perception

Preference Fit Low-interest articles were generally rated lower in preference fit than high-interest articles (Study 2: $M_{low} = 2.66, SD_{low} = 1.24; M_{high} = 3.58, SD_{high} = 1.13$).

Article Characteristics Overall, participants rated the high-interest article recommendations higher in perceived constructiveness, relevance, trustworthiness and understandability than they rated the low-interest recommendation. A descriptive analysis comparing the responses for low-interest articles with and without explanations (see Table 3) showed similar mean ratings for all measures, with slightly higher ratings for the explanation condition in perceived trustworthiness and understandability. These higher ratings could be found specifically for IRR and DIS conditions. Perceived constructiveness and relevance were rated slightly higher for the condition showing no explanations.

4.4. Explanation Perception

Participants in Study 2 rated explanations higher than participants in Study 1 across most evaluation measures and explanation conditions (see Figure 4). Across both studies, explanations were rated highest in terms of understandability ($M = 3.84 - 3.89, SD = 0.82 - 0.83$), followed by perceived usefulness ($M = 3.45 - 3.71, SD = 1.06 - 1.08$). Regarding preference for more similar explanations, ratings remained moderate in both studies, slightly increasing in Study 2 ($M = 3.25, SD = 1.19$) compared to Study 1 ($M = 3.02, SD = 1.22$). Ratings were lower and more diverse between studies for attention-grabbing (Study 1: $M = 2.91, SD = 1.32$, Study 2: $M = 3.26, SD = 0.82$) and influence on selection (Study 1: $M = 2.91, SD = 1.25$, Study 2: $M = 3.23, SD = 1.26$).

When comparing individual explanation strategies, IRR and DIS received higher ratings across several measures, particularly for perceived usefulness and influence on selection. This pattern was more prevalent in Study 2 than in Study 1.

To examine whether the perceived attention-grabbing quality influences article choice, we conducted a mixed-effects logistic regression predicting the selection of low-interest articles from attention ratings, with participant as random intercept. Results showed a significant effect of attention on selection (e.g., Study 1: $\beta = 0.71, SE = 0.15, z = 4.77, p < 0.001$), indicating that explanations that caught participants' self-reported attention more were associated with a higher likelihood of low-interest recommendation selection. Each one-point increase in attention rating approximately doubled the odds of selecting the low-interest article (e.g., Study 1: odds ratio ≈ 2.04). Predicted probabilities for low-interest selection in Study 1 increased from 5.3% at the lowest attention level to 49.5% at the highest level, which is also reflected in the descriptive results (6.1% $\rightarrow$ 45%).

Similar results were observed for participants' LRF. A linear mixed-effects model showed a positive significant effect of attention on LRF (e.g., Study 2: $\beta = 0.71, SE = 0.13, p < 0.001$), indicating higher attention to be associated with higher LRF. In contrast, there were no significant effects of explanation type or interaction effects between attention rating and explanation type on LRF (all $p > 0.05$).

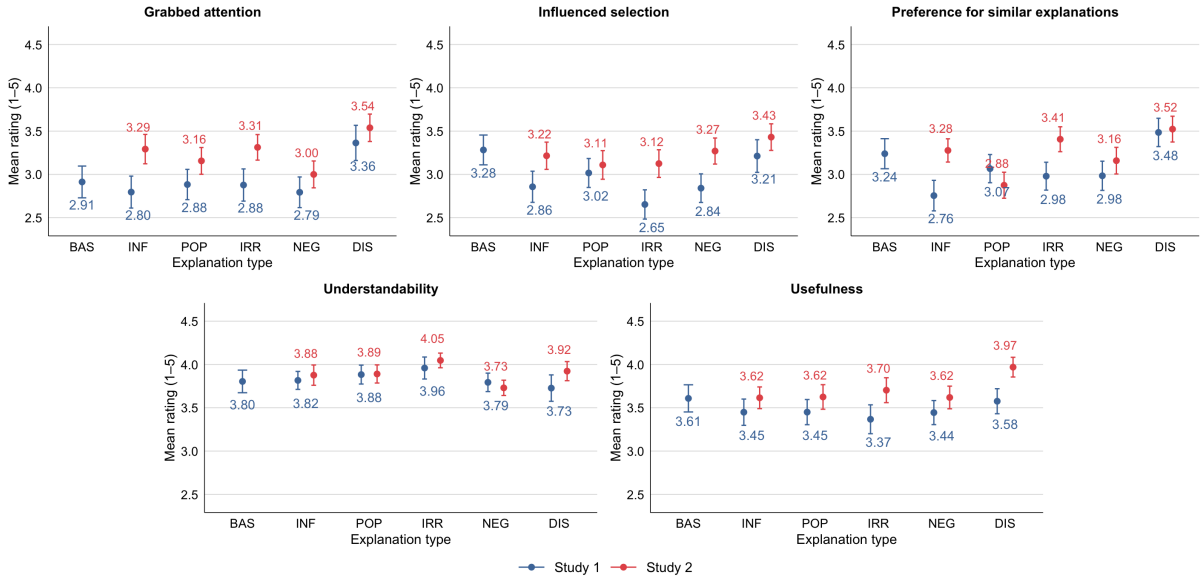

Figure 4: Perception ratings per explanation type (*BAS* = Baseline explanation): Understandability and usefulness received strongest scores; Study 2 evaluations mostly outperformed those from Study 1 across explanation types

5. Discussion

Overall, the findings show that the explanations did not significantly increase the selection of low-interest news articles, compared to baseline (Study 1) or no-explanation (Study 2) conditions, though they suggest certain descriptive differences between explanation types. Additionally, explanation ratings increased from Study 1 to Study 2, and explanations with higher perceived salience ratings were associated with higher LRF and a higher likelihood of selecting the related low-interest article.

Addressing *RQ1*, the findings show that none of the needs-based explanations could bridge readers' "interest-gap" in article selection behavior. This suggests that textual explanations alone may not be effective enough to overcome already established topic preferences and is supported by the observed gaps between low- and high-interest article selection rates and LRF in both studies. Explanations addressing *IRR* showed descriptively stronger results than the other explanations, across both studies. This might be connected to the fact that perceived irrelevance was also one of the most frequently reported news avoidance reasons.

Regarding demographics as potential moderating factors, age and gender differences in low-interest article selections were not significant, which suggests that the explanations generally didn't affect demographic groups differently in the studies' setup. However, the reported age group differences in news platform popularity confirm the contrast in news consumption habits between younger and older generations.

While the needs-based explanations showed limited effects on low-interest article selection, they revealed clearer insights into how recommended articles and explanations were perceived. Addressing *RQ2*, high-interest articles were generally rated higher in preference fit, perceived article constructiveness, relevance, trustworthiness and understandability than low-interest articles, further demonstrating the persistent "interest gap". At the same time, recommendations accompanied by the *IRR* explanation again received higher scores for perceived trustworthiness and understandability, as well as to some extent the *DIS* explanation. The latter pattern may be partly explained by the fact that the measurement of perceived trustworthiness is directly addressed by the explanation.

Looking beyond the perception of the recommended articles, there are also insights into how the needs-based explanations were perceived. Overall, the explanations were rated as understandable and useful, which suggests that the concept of needs-based explanations was generally easy to understand and adapt to. Also, on average, participants answered positively to the statement whether they would like to see more of explanations like these. As these positive explanation perceptions did not translate

into significantly higher overall selection rates, it suggests that a favorable explanation impression is not enough to change article choice.

One of the clearest findings across both studies is the role of explanation salience in article choice. Explanations that were perceived as more "attention-grabbing" were associated with both higher LRF ratings and a higher likelihood of choosing the low-interest article, which proposes that the effectiveness of needs-based explanations is less dependent on whether they are present or not, but rather on whether they are noticed and then processed adequately in the decision-making process. Moreover, the higher explanation ratings combined with higher overall low-interest article selection rates in Study 2, compared to Study 1, may further indicate that explanation perception depends on the visual presentation and salience, apart from only text-based aspects.

Lastly, descriptive differences in selection rates across news types suggest that needs-based explanations may have a somewhat stronger effect for soft news compared to hard news, although this was not of statistical significance. The selection rates broadly showed a similar pattern to the LRF ratings across topics, suggesting that news categories with a higher self-reported likelihood to read the full article generally also tended to be selected more. At the same time, some topic-specific deviations indicate that article selection and LRF do not fully overlap.

6. Limitations and Future Work

This work has several limitations. First, both experiments captured only two short-term interaction rounds in a controlled setting, and participants were not previously familiar with needs-based explanations. The observed effects might therefore differ in longer-term, real-world settings, where readers are repeatedly exposed to such explanations and may become more accustomed to them over time. Furthermore, participants could not verify for themselves whether the explanations accurately reflected the recommended articles. Over time, however, the perceived accuracy of explanations may affect both readers' trust in the recommendations as well as their article selection behavior. Future research could therefore examine needs-based explanations in longitudinal settings to better understand how factors like perceived explanation accuracy and familiarity, repeated exposure, and a more realistic context shape readers' article perceptions and reading behavior.

Second, although both studies addressed the same research questions, there were some differences in their setup which were mostly in the presentation of the explanations. Moreover, because the randomization of assigned explanation conditions across participants and rounds was not fully controlled in Study 1, the distribution of conditions was not always balanced. This limited the interpretability of some inferential analyses, which were then conducted only for Study 2. At the same time, descriptive patterns were largely comparable across both studies, suggesting a consistent overall trend in the findings.

Third, the study design created a strong contrast in topic preference between the two news article recommendations in each round, as they represented participants' previously selected most favorite and least favorite news categories. As a result, the observed effects may reflect a rather strict setting for needs-based explanations to influence article selection behavior. Future work could therefore examine whether needs-based explanations are more effective when low-interest recommendations are compared with topics of more moderate interest, where the preference gap is smaller.

In addition to these limitations, the findings also point to directions for further research. As the results show that higher perceived explanation salience is associated with higher low-interest article selection rates, future studies could examine whether alternative visual presentations of the explanation intervention lead to stronger behavioral effects. Furthermore, future work could explore whether other explanation formats or additional, broader visual interface-based interventions would be more effective in promoting engagement with low-interest news articles. Finally, because Social Media was reported as the main news consumption platform among the majority of the younger participants, testing needs-based explanations in an interface that more closely resembles social media environments might provide further insights into how younger audiences perceive and respond to such explanations.

7. Conclusion

This work investigated in two studies whether needs-based explanations can reduce readers' selective news avoidance when applied to low-interest news recommendations in a personalized setting, and how such explanations shape the perception of the recommended articles. Using a mixed design, we measured both behavioral outcomes, including low-interest article selection rates and the self-reported likelihood of reading the full article, as well as participants' subjective evaluation of the explanations and recommendations across different explanation strategies and news topics.

In contrast to the hypothesized effect of needs-based explanations on readers' news selection behavior, the findings suggest that such explanations alone are not sufficient to significantly reduce selective news avoidance. Nevertheless, this rather unexpected result offers valuable insights, for instance, into deciding factors for behavioral effects of explanations, in particular explanation salience. More broadly, it implies that future explanation design for news recommendations should focus not only on the explanation content, but also on the visual presentation and interface integration. The findings further show the need for a more holistic approach to tackle selective news avoidance, since news avoidance and its underlying drivers are complex [10, 38] and likely cannot be addressed through a single interface element, like explanations, alone.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-5 in order to: Improve writing style. After using the tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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