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Reliance on AI-Driven Recommendations on Netflix: An Integration of the Heuristics-Systematic Model with Human Agency Factors

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ABSTRACT

AI-driven recommendation algorithms are a signature feature of video streaming services and ideally contribute subscribers' utility. However, that is not always the case. Given the default nature of recommendation algorithms, this study investigated the antecedents of reliance on recommendation algorithms by integrating the heuristic-systematic model with motivational orientations. A survey of 497 U.S. Netflix users revealed that the perceived accuracy and diversity of algorithmic recommendations, trust in AI, and attachment to the streaming platform increase algorithm reliance. Further, the perceived accuracy of recommendation algorithms has a stronger effect on algorithm reliance for those who have a greater attachment to the platform.

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Streaming is the predominant way to access video content in the United States (U.S.) (Wile, 2025). Thanks to its unlimited shelf-space, users of video streaming services are offered have access to a wide range of content options. They leverage artificial intelligence (AI) so as to recommend relevant videos to their users partially based on users' previous viewing histories. However, a recent survey of U.S. video streaming subscribers surprisingly shows that U.S. video streaming users spend about 110 hours per year searching for what to watch. Further more than 50% of users experience algorithm fatigue from the overwhelming amount of content that is recommended by these algorithms (UserTesting, 2025).

Recommendation algorithms are *decision* support systems rather than fully automated systems because users of video streaming services have discretion over 1) whether or not they embrace the recommendation algorithms and 2) how heavily they do rely on them to select specific video content to watch. Apart from the prevalence of AI-powered recommendation algorithms (hereinafter, recommendation algorithms) and their very built-in nature, some

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users are not satisfied with them and are less likely to rely on them. However, little is yet known about why. Given this backdrop, this study illuminates the antecedents of viewer reliance on recommendation algorithms in the context of video streaming services. Building on the heuristic-systematic model, this study theorizes that the quality perceptions of recommendation algorithms and attitudes toward AI influence the reliance on recommendation algorithms. Taking the uses and gratifications (U&G) perspective, this study also argues that human agency does impact the level of reliance on recommendation algorithms. Thus, this study integrates video streaming service users' attachment to a video streaming platform and content with locus of control in predicting algorithm reliance. To achieve these goals, this study uses a survey and collect data from U.S. Netflix users. Netflix was chosen because it is a leading U.S. video streaming service whose recommendation algorithms have become the backbone of its business model (Gomez-Urbe & Hunt, 2015; Netflix, n. d).

The contributions of this study are fourfold. First, it focuses on a video streaming service. Surprisingly, despite the importance of recommendation algorithms for video streaming services, scant research has yet tackled the issue in this context. Most of the prior studies have focused on recommendation systems in the context of e-commerce (e.g., Cabrera-Sánchez et al., 2020; Jin & Zhang, 2023; Yoon & Lee, 2021). Second, this study centers on the *reliance* on AI recommendations. Media reliance refers to "the degree to which a medium is important to the acquisition of information used by the individual" (Pierce et al., 1990, p. 838). A medium or technology ultimately becomes more influential to audiences if those audiences increasingly *rely* on it (Miller & Rcese, 1982). Video streaming service users are *repeatedly* exposed to algorithmic recommendations because that feature is provided as a default. Therefore, reliance is a crucial construct that shapes the actual platform usage patterns. In terms of recommendation algorithms, prior studies have focused primarily on affective or emotional responses, such as satisfaction or attitudes (e.g., Jin & Zhang, 2023; Nanou, Lekakos, & Fouskas, 2010; Nguyen et al., 2018). Little attention has been paid to the behavioral use of such recommendation algorithms. Thus, third, this study's survey of users will complement the findings of those extant studies that have predominantly taken computational or experimental approaches. This survey approach will shed light on how users' *perceptions* of recommendation algorithms and AI influence video streaming service users' reliance on recommendation algorithms. Fourth, this study tackles how human agency factors influence video streaming service users' reliance on recommendation algorithms. The use of recommendation algorithms may not be entirely dependent on the characteristics or quality of recommendation algorithms; users' motivational orientations toward the *platform* and *content* and *control perception* in their lives may also influence their algorithm reliance. However, prior studies neglected these

human agency factors. Therefore, this study's integration of such human agency factors will enrich our overall understanding of the use of recommendation algorithms.

Theoretical foundations

This study elucidates the underlying reasons for why some people rely heavily on recommendation algorithms, whereas others are less likely to do so through the integrated lens of the heuristic-systematic model and the U&G perspective.

The heuristic-systematic model

The heuristic-systematic model suggests that individuals take two separate routes – systematic and heuristic processing – in their decision making (Chaiken, 1980). The first route is systematic processing, a *central* information processing route that involves a *rational* evaluation of the offered information (Chaiken, 1980; Tam & Ho, 2005). Recipients of a message will thus carefully evaluate the message itself, such as its quality and content, prior to embracing it (Natarajan & Periaiya, 2024). The second route is heuristic processing, a mental shortcut or rule of thumb that enables individuals to make a quick judgment without making rational evaluations based on limited information cues (Chaiken, 1980). When individuals are exposed to a message or information, their acceptance of that message is influenced not only by central cues, such as the message itself, but also by peripheral cues, such as the identity of the source that is not directly related to the message itself (Chaiken, 1980; Kahlor et al., 2003). That is, the characteristics of the source where the message was generated are heuristics that influence the acceptance of the message. The liking of that source and trust in that source can influence the acceptance of the message, even though those perceptions are not directly related to the substance of the message. Heuristics reflect stereotypes or biases that might influence people's decision-making (Gelman & Legare, 2011; Sundar, 2020).

Human agency in content searching and viewing

U&G theory posits that audiences actively choose and use particular media or content to fulfill their specific needs (Blumler, 1979; Rubin, 1983). Audience *activeness* is an important tenet of the U&G theory. During the content selection process, *active* audiences are more likely to have clear ideas about what to watch to fulfill their needs (Blumler, 1979). In terms of the use of video streaming services, some users may be substantially attached to *content* and thus actively will search for a specific television show or movie across video platforms. In contrast, other users may be

more attached to a specific video streaming platform as a *medium* and then habitually use that platform. It is thus conceivable that the former group makes more conscious and intentional decisions about their content selections than does the latter, so as to fulfill their psychological needs associated with content consumption. Therefore, this study argues that such differences in attachment to either a medium or content can help predict the levels of reliance on AI recommendations.

Video streaming services provide users with recommendation algorithms as a default. However, these algorithms are not fully automated, so users still can exert some level of active control as to whether they select a video recommended by the algorithms and how heavily they rely on them. Nevertheless, the automated nature of recommendation algorithms undeniably takes away from the users some levels of *activeness and human agency*. Hence, this study also theorizes that the locus of control, which refers to “one’s belief in the relative power to control events in one’s life” (Haridakis & Hanson, 2009, p. 320), will influence video streaming service users’ reliance on recommendation algorithms.

Hypotheses and research questions development

Attachment to medium or content

U&G studies have found that different audiences can be classified according to the degree to which they are attached to a medium (Adams, 1992; Perse, 1990; Rubin, 1977) or to content (Lin et al., 2016, 2018). Attachment to the *medium* refers to the degree to which individuals feel lost or uncomfortable without that medium (Adams, 1992). In the pre-streaming era, habitual viewing was strongly associated with television attachment (Rubin, 1979). In contrast, attachment to *content* refers to the degree to which individuals choose and consume a specific program because they are emotionally connected to the content. In the same vein, by focusing specifically on social media use, Blackwell et al. (2017) found that social media attachment is also strongly associated with usage patterns and addiction.

In the U.S., video streaming services face fierce competition. Given the increasing number of video streaming platforms, consumers have thus increased their bargaining power. From a video streaming platform’s perspective, it is important to retain existing users and understand how heavily they are relying on recommendation algorithms. Those persons who are more attached to a medium are expected to use a video streaming platform habitually and consume one piece of video content after another; attachment to the medium, therefore, makes the choice of specific content less important for them. Therefore, the tendency to be attached to a video streaming platform as a *medium*

leads them to rely heavily on algorithmic recommendations. In contrast, those who are more attached to *content* actively search for the specific content that they desire. Therefore, this study expects them to rely less on recommendation algorithms and thus proposes two hypotheses:

Hypothesis 1a. Attachment to the video streaming platform is positively associated with reliance on recommendation algorithms.

Hypothesis 1b. Attachment to content is negatively associated with reliance on recommendation algorithms.

Locus of control

Locus of control refers to “one’s belief in the relative power to control events in one’s life” (Haridakis & Hanson, 2009, p. 320). It reflects one’s capability to affect oneself and others (Rubin, 1993). Those who are internally controlled are inclined to believe that they have the ability to control external events, whereas those who are externally controlled believe that their lives are more controlled by external events (Lefcourt, 1983; Levenson, 1974). Locus of control is also directly related to the U&G theory in that the latter assumes that audiences actively choose media or content to fulfill their needs and control their actions (Rubin, 1993).

Locus of control influences the motives for communication and behavior (Brenders, 1987; Haridakis & Hanson, 2009). Internals, those who have a higher locus of control, are motivated to actively seek out greater control and put more effort into situations where they have control (Brenders, 1987). Prior studies also suggest that locus of control affects people’s reliance on automation and their reactions to the own ability to intervene in decision-making (Brownell, 1981; Rudin-Brown & Parker, 2004; Sharan & Romano, 2020). Using a card game experiment, Sharan and Romano (2020) found that internals rely less on suggestions from AI algorithms and other humans in the game because they wanted more control over their decisions. In the context of video streaming services, recommendation algorithms limit the users’ explicit role in finding the content they want. Those who are internally oriented will demand more control over content selection and are more proactive in searching for the content they want. Thus, this study argues that they rely less on recommendation algorithms and proposes the following hypothesis:

Hypothesis 2. Internal control is negatively associated with reliance on recommendation algorithms.

Systematic processing: recommendation quality

In the context of recommendation algorithms on video streaming services, users have quality perceptions about recommendation algorithms. Quality perceptions represent systematic, central routes in that they are directly related to the performance of the recommendation algorithms and video streaming service users rationally assess the quality of such algorithms. Computational studies on the quality improvement of recommendation algorithms have thus focused on accuracy, diversity, or novelty (Herlocker et al., 2004; Lu et al., 2015; Silveira et al., 2019; Zhou et al., 2010). However, ordinary users of video streaming services do not scientifically analyze these tenets. Instead, they build perceptions, and these perceptions, as opposed to actual accuracy, diversity, and novelty, are expected to influence their use of recommendation algorithms. Surprisingly, little research has yet empirically investigated the impact of such perceptions on the behavioral use of recommendation algorithms.

The perceived accuracy of algorithmic recommendations

There are a variety of methods for developing recommendation algorithms. What they have in common is that they are designed to find the similarity of users or objects or both (Zhou et al., 2010). For instance, Amazon's algorithmic recommendations are based on an examination of how similar users' purchase histories and browsing activities are (Linden et al., 2003; Schafer et al., 2001). Because of the importance of that similarity in understanding recommendation systems, how accurately an algorithm predicts a user's preferences has been considered key to effective recommendation algorithms (Herlocker et al., 2004; Zhou et al., 2010).

Machines have also been viewed as accurate because humans perceive them as being free of errors (Skitka et al., 1999; Yang & Sundar, 2024). However, securing accuracy is challenging for recommendation algorithms on video streaming platforms because videos are experience goods. People's preferences for video content can and will also change over time. Those preferences are influenced by social pressures, moods, season or time of day, and other external factors. The impact of accuracy on satisfaction with recommendation algorithms is mixed. Focusing on recommendation systems for e-Commerce, Kim et al. (2021) found that the accuracy of recommendation systems positively affects satisfaction with recommendation systems. Similarly, in the context of video streaming services, Kwon et al. (2021) found that the perceived accuracy of algorithmic recommendations was positively associated with perceived diagnosticity, which refers to the extent to which consumers' experiences with matched scores are helpful for overall product evaluations. In contrast, other studies have suggested that overly accurate recommendations generate what is known as a "similarity hole" (Chen et al., 2022; Herlocker

et al., 2004; McNee et al., 2006) and diminish the satisfaction with recommendation algorithms (Bobadilla et al., 2013).

Reliance on recommendation algorithms differs from affective responses, such as satisfaction with them, in that reliance reflects behavioral use. With regard to video content, individuals have content preferences (Rowland et al., 1989). With the plethora of content options available, accurately predicting users' preferences may be the most appealing feature sought from recommendation algorithms. Accuracy of predicting interests based on the similarity between subscribers' past histories and the recommended items is the backbone of recommendation algorithms when reducing users' search costs (Smyth & McClave, 2001). Therefore, the current study expects the perceived accuracy of recommendation algorithms to increase algorithm reliance and proposes the following hypothesis:

Hypothesis 3a. The perceived accuracy of algorithmic recommendations is positively associated with reliance on recommendation algorithms.

Video streaming service users who are attached to a platform as a *medium* tend to stick to that platform rather than being selective in content due to their habitual use of the platform. Therefore, this study expects the perceived accuracy of recommendation algorithms to be less important for those who are attached to a video streaming platform. In contrast, the accuracy of recommendation algorithms is expected to be more important for those who are attached to content, because they are attached to a specific television show or movie. Thus, this study proposes the following two hypotheses:

Hypothesis 3b. The effect of perceived accuracy on reliance on recommendation algorithms is weaker for those who have a greater attachment to the video streaming platform.

Hypothesis 3c. The effect of perceived accuracy on reliance on recommendation algorithms is stronger for those who have a greater attachment to content.

The perceived diversity of algorithmic recommendations

Diversity as a measure of quality for recommendation algorithms refers to "the degree of differentiation among recommended items" (Bobadilla et al., 2013, p. 118). Ziegler et al. (2005) found that diversity, along with accuracy, affects the satisfaction with recommendation systems. Similarly, Ekstrand et al. (2014) found that the diversity of algorithmic recommendations positively predicts users' choice of recommendation systems for films. In

contrast, a computational analysis by other studies have pointed out there is a trade-off between accuracy (or similarity) and diversity. Smyth and McCave argued that focusing on extreme similarity can lower diversity. In the same vein, Zhou et al. (2010) suggested that accuracy and diversity should be balanced because stressing diversity too much in recommendation algorithms can weaken accuracy. Although prior studies have tried to find the effect of diversity on consumer attitude and behavior, most of them have taken computational approaches. However, video streaming service users' decisions to use recommendation algorithms likely depend on *perceptions* rather than *actual* performance because they do not thoroughly examine the latter. Nevertheless, little is known yet about how video streaming service users' *perceived* diversity, rather than actual diversity, affects their use of and reliance on recommendation algorithms. Therefore, this study asks the following research question:

RQ1. How is the perceived diversity of algorithmic recommendations associated with reliance on recommendation algorithms?

The perceived novelty of algorithmic recommendations

The novelty of algorithmic recommendations is defined as “the degree of difference between the items recommended to and known by the user” (Bobadilla et al., 2013, p. 118). Novelty focuses on how pieces of information or content differ from “what has been previously seen by a specific user,” whereas diversity focuses on how the recommended items are different from each other (Vargas & Castells, 2011). Content-based and collaborative filtering are both widely used methods for algorithmic recommendations (Victor et al., 2011). Content-based methods recommend videos that are similar to the ones that have already been watched by a particular user, whereas collaborative filtering methods focus on recommending videos that are based on other users who have similar tastes to a specific user

(Bobadilla et al., 2013; Victor et al., 2011). The pitfall of these recommendation algorithms is that these methods limit users' opportunities to be exposed to videos they have not ever thought of, and the computational studies argue that the value of recommendation algorithms lies in the discovery of niche items that the users themselves cannot readily discover (Abdollahpouri et al., 2021; Herlocker et al., 2004).

The results of prior studies regarding novelty are mixed. Sinha and Swearingen (2001) found that online recommender systems are preferred to friends' recommendations because algorithms recommend items that users have not been exposed to yet. In contrast, an experiment involving a movie recommendation website revealed that the novelty of the recommended items

negatively predicts satisfaction with the website (Ekstrand et al., 2014). Focusing on video streaming service users' reliance on recommendation algorithms to understand behavioral patterns, this study empirically examines how *perceived* novelty affects such reliance and poses the following research question:

RQ2. How is the perceived novelty of algorithmic recommendations associated with reliance on recommendation algorithms?

Heuristic processing: AI as a recommendation source

Regarding heuristic processing, Chaiken (1980) suggests that how individuals judge information is influenced not only by the information itself, but also by the characteristics of the source. For example, if people notice that a message comes from an expert, they will perceive it as more credible and not because the message itself is true, but because it has been sourced from an expert (Sundar et al., 2008). Lay persons do not understand the underlying mechanisms of recommendation algorithms, but they do understand that recommendations in video streaming services are generated by AI and not by humans. Algorithmic recommendations are generated by AI and, this study theorizes that users' stereotypes of AI, as heuristics, influence the reliance on recommendation algorithms. Attitudes are based on both cognition and affection (Zanna & Rempel, 1988) and are shaped by both trust and liking (Feng & MacGeorge, 2010; Perloff, 2008). Trust relies more on cognition, whereas liking relies more on affect (Crites et al., 1994; Yang & Yoo, 2004).

Trust in AI

Trust is one of the main issues that individuals encounter when interacting with other humans, media, or machines. With respect to human-computer interactions (or human – human interactions), Morgan and Hunt (1994) defined trust as having a “perceived confidence in the exchange partner’s reliability and integrity” (p. 23). Trust plays a vital role in any situation where people experience uncertainty. Trust is crucial in predicting the intention to use and also the actual use of technology (Kim et al., 2020; Seegebarth et al., 2019).

Source trust is a heuristic that influences the message recipient’s acceptance of that message. On video streaming services, users consciously and unconsciously recognize that the recommendations are made by AI, not by humans. Studies have found that trust is actually positively associated with reliance on machines (Parasuraman et al., 2008) and automation (Hoffman et al., 2018). In

contrast, Lee (2018) found that people perceive algorithms as being less trustworthy in the context of human tasks, as these tasks require an understanding of emotions and social nuances and are different than mechanical tasks, which are associated with data processing for objective decision-making. Given the plethora of content options, recommending the right video content at the right time is a complex process because videos are experience goods.

Given the uncertainty and risk of AI that is derived from its newness, trust in AI increases one's confidence in AI applications and mitigates the uncertainty about their performance and integrity. Trust is an attitude, whereas reliance is behavior (Lee & See, 2004). Therefore, the present study proposes that trust in AI recommendations as an attitude that influences the reliance on AI recommendations as behavior. This study posits the following hypothesis:

Hypothesis 4a. Trust in AI is positively associated with reliance on recommendation algorithms.

Those who have a higher internal locus of control also will demand more control over external events. Thus, this study expects trust to be more important in determining video streaming service users' reliance on recommendation algorithms for such individuals, and this study postulates the following hypothesis:

Hypothesis 4b. The effect of trust in AI on reliance on recommendation algorithms is stronger for those with a higher internal locus of control.

Distrust in AI

Distrust is a construct that is distinct from trust because the two are not merely opposites, even though distrust is indeed negatively associated with trust (e.g., Kaplan et al., 2023; Lewicki et al., 1998; Liu & Wang, 2010; Saunders & Thornhill, 2004; Sitkin & Roth, 1993; Van De Walle & Six, 2014). Distrust is a perception that another party may possibly harm one (Liu & Wang, 2010). Thus, distrust induces one to "buffer oneself from the effects of another's expected conduct" (Lewicki et al., 1998, p. 439). Therefore, both trust and distrust in AI should be taken into account to fully assess how individuals perceive the trustworthiness of AI (Kaplan et al., 2023; Noah & Sethumadhavan, 2019).

Despite the benefits of AI, humans do question the degree to which machines can perform intricate human functions (Castelo et al., 2019). Studies have also documented that distrust toward AI influences attitudes toward or use of various AI systems, including chatbots for customer search and AI-assisted health tools (Adams et al., 2020; Haan et al., 2019; Kang et al.,

2023). Given that lay people do not understand how recommendation algorithms work, the present study argues that distrust in AI acts as a mental shortcut that helps determine how heavily video streaming service users rely on recommendation algorithms. This study expects that distrust in AI to transcend to recommendation algorithms, so it will lower algorithm reliance and proposes the following hypothesis:

Hypothesis 5a. Distrust in AI is negatively associated with reliance on recommendation algorithms.

Regarding the locus of control, those who have a higher internal locus of control are inclined to seek out their own control of situations. Heavy reliance on recommendation algorithms translates to forgoing human agency to actively searching for the content that individuals want. Thus, this study expects distrust in AI to disproportionately affect users with a higher internal control, and this study thus argues that the effect of distrust in AI on algorithm reliance is more pronounced for those who have a higher internal control. Thus, the following hypothesis is proposed:

Hypothesis 5b. The effect of distrust in AI on AI-powered recommendations is stronger for those who have a higher internal control.

Liking AI

Attitude is shaped not only by one's cognitive elements, but also by affect (Zanna & Rempel, 1988). Studies have documented that liking, as an affect construct, influences the acceptance or adoption of a substance. Liking is defined as a user's fondness for an object or human based on the positive perceptions of them or experiences (Allothman et al., 2017). Chaiken (1980) found that humans use the likability of a communicator, namely, source likability, as a heuristic in deciding whether to accept a message from a person. In the same vein, by applying a heuristic processing model to videoconferencing, Ferran and Watts (2008) found that individuals' acceptance of information is more affected by the source characteristics, specifically by how much they like the speaker, rather than by the actual quality of the information the speaker provides. Yoon and Meyvis (2024) also found that the consumption levels of a particular product are primarily influenced by how much individuals like it. Building on these findings of the extant studies, this study proposes that the liking AI as a source of

recommendations will positively influence algorithm reliance. Thus, this study posits the following hypothesis:

Hypothesis 6. Liking AI is positively associated with the reliance on recommendation algorithms.

Methods

Data collection

This study used a survey to test the hypotheses and answer the research questions. Netflix was chosen to examine reliance on recommendation algorithms because Netflix is a pioneer in video streaming services and its business model is built around recommendation algorithms (Gomez-Uribe & Hunt, 2015; Netflix, n. d.). Netflix users 18 years old and older in the U.S. were recruited via Prolific, an online crowdsourcing platform. With no publicly available information about Netflix users in the U.S., this was a convenient sampling approach. A few filter options provided by Prolific (i.e., current country of residence, age, and Netflix subscription) were used to locate U.S. Netflix users. Participants were paid \$1.53 for a 10-minute completion time. Responses from 497 Netflix users in the U.S. were analyzed. Female participants made up 53.4% of the survey participants. The mean age of the survey participants was 40.20 ($SD = 12.78$). Regarding ethnicity, Caucasians and African Americans made up 69.6% and 18.1% of the participants, respectively; Asians and Hispanics made up 4.2% and 4.8% of the participants, respectively. The descriptive statistics also showed that 57.5% of these participants use Netflix often, whereas 29% said they use it all the time. Regarding the primary platform used to access video content, 76.9% of the participants chose streaming as their primary way to watch television shows, whereas 13.5% chose pay television, such as cable/satellite TV services.

Measures

[Appendix](#) shows the measurement items that were used for each construct, along with the descriptive statistics for each construct. All measurement items were measured on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree) except for the ones noted separately. Reliability of the measurement items is also reported in [Appendix](#).

Dependent variable

Reliance on recommendation algorithms ($M = 3.35$, $SD = .96$) was the dependent variable. Before asking about reliance on recommendation

algorithms, the survey provided a brief explanation about Netflix's use of recommendation algorithms to suggest television shows and movies that Netflix users may be interested in viewing. Following that explanation, participants were asked to indicate how much they relied on recommendation algorithms to choose videos on Netflix on a five-point scale (1 = never rely; 5 = heavily rely) and how important recommendation algorithms are when they are selecting videos on Netflix on a five-point scale (1 = not at all important; 5 = very important). That measure was adapted from Cha (2024), Johnson and Kaye (2015), and Pierce et al. (1990).

Independent variables

Independent variables included platform attachment, content attachment, internal locus of control, the perceived accuracy, diversity, and novelty of recommendation algorithms, trust in AI, distrust in AI, and the liking of AI.

Platform attachment was measured via five measurement items that included "I would rather watch Netflix than do anything else" and "I would feel lost without Netflix," which were adapted from Rubin and Rubin (1982) and Rubin et al. (1994). *Content attachment* was measured using five similar measurement items, but these focused on the attachment to each participant's favorite television program that they currently watch. Examples of measurement items included "I would rather watch my favorite television program than do anything else" and "Watching my favorite television programs is one the more important things I do each day." The descriptive statistics showed that Netflix platform attachment ($M = 3.03$, $SD = 1.101$) was higher than content attachment ($M = 2.91$, $SD = 2.91$).

Internal locus of control ($M = 3.71$, $SD = .50$) was measured using 28 items that were developed by Duttweiler (1984). The frequency of the survey participants' usual attitude toward each of the 28 statements was measured on a five-point scale (1 = rarely; 5 = usually). The measurement items included "I _____ like to have a say in any decisions made by any group I'm in," and "I _____ am sure enough of my opinions to try and influence others." A summated scale was created, following the scoring guidelines suggested by Duttweiler (1984).

Perceived accuracy of the recommendation algorithms ($M = 3.94$, $SD = .72$) was measured through the three items adapted from Coppens et al. (2023), Pu, Chen, and Hu (2011), and Choi et al. (2017), including "The videos recommended by Netflix algorithms match my interests" and "The videos recommended by Netflix algorithms suit my interests."

Perceived diversity of the recommendation algorithms ($M = 3.92$, $SD = .56$) was measured, using four items based on Napoli (1999) and Tintarev et al. (2013). Specific measurement items included "Netflix algorithms recommend

videos for me based on various topics” “Netflix algorithms recommend videos for me based on various themes.”

Perceived novelty of recommendation algorithms ($M = 3.91$, $SD = .85$) was measured using three items, including “Netflix algorithms recommend videos I do not expect” and “Netflix algorithms recommend videos I would not have thought to consider.” These measurement items were adapted from Pu, Chen, & Hu (2011).

Trust, distrust, and liking focused on attitudes toward AI in general. A brief definition of AI was provided to survey participants before measuring these constructs as follows: “AI can execute tasks that typically require human intelligence without human intervention. It enables machines to sense, act, learn, and adapt in an autonomous, human-like way. AI may be part of a computer or online platform – but it can also be encountered in various other hardware devices such as robots” (Stein et al., 2024, p. 13).

Trust in AI ($M = 3.42$, $SD = 1.07$) was measured through seven items, including “AI has integrity,” “AI is reliable,” and “AI provides security.” *Distrust in AI* ($M = 1.89$, $SD = .97$) was measured through five items, including “AI is deceptive” and “AI’s action will have a harmful or injurious outcome.” The measurement items for both trust and distrust in AI were borrowed from Scharowski et al. (2024). The survey participants was asked to indicate how each statement best describes their feeling or impression of AI on a 5-point scale (1 = not at all; 5 = extremely).

Liking of AI ($M = 4.12$, $SD = .92$) was measured through four items, including “When I think about AI, I have mostly positive feelings” and “I have strong negative emotions about AI.” Some of the measurement items were reverse coded like the latter one here. These measurement items were borrowed from Stein et al. (2024).

Results

Ordinary least squares (OLS) regressions were carried out for the data analysis. Table 1 shows the results of the OLS regressions. Before regression analyses were performed, the variables used to created interaction terms were mean-centered to prevent multicollinearity (Day & Wensley, 1988). Those variables included platform attachment, content attachment, locus of control, the perceived accuracy of recommendation algorithms, trust in AI, and distrust in AI. The variation inflation factors (VIF) were checked to rule out any possible multicollinearity. The VIFs ranged from 1.02 to 3.49 across the research models, ruling out a multicollinearity issue. Model 1 included only control variables (i.e., demographic variables). Model 1 explained 15% of the variance in reliance on recommendation algorithms. For Model 2, independent variables were entered. The independent variables were platform attachment, content attachment, internal locus of control, systematic processing variables

Table 1. OLS regression of algorithm reliance.

	Model 1			Model 2			Model 3			Model 4		
	B	SE	β	B	SE	β	B	SE	β	B	SE	β
Constant	4.169***	.163		3.652***	.121		3.621***	.121		3.645***	.121	
Age	-.013	.003	-.167***	-.005	.002	-.064*	-.005	.002	-.060	-.005	.002	-.066
Male	-.011	.082	-.006	-.045	.060	-.023	-.060	.060	-.031	-.056	.060	-.029
Less than high school	-2.271	.637	-.152***	-1.066	.470	-.071*	-1.018	.468	-.068*	-1.076	.469	-.072*
High school	-.723	.120	-.285***	-.166	.094	-.066	-.173	.094	-.069	-.164	.094	-.065
College	-.450	.092	-.234***	-.126	.069	-.066	-.132	.069	-.069	-.130	.069	-.068
African American	.234	.108	.095*	.032	.079	.013	.032	.078	.013	.036	.079	.014
Asian	-.161	.201	-.034	.058	.147	.012	.074	.146	.016	.073	.147	.015
Hispanic	-.138	.190	-.031	-.078	.136	-.018	-.071	.136	-.016	-.076	.136	-.017
Multiracial	-.015	.370	-.002	.062	.266	.007	.099	.266	.011	.088	.266	.010
Platform attachment				.153	.050	.162**	.146	.050	.155**	.155	.050	.165**
Content attachment				.087	.048	.089	.083	.048	.084	.077	.048	.078
Internal locus of control				-.008	.065	-.004	-.007	.065	-.004	-.016	.065	-.008
Recommendation accuracy				.454	.054	.343***	.492	.057	.371***	.478	.056	.360***
Recommendation diversity				.170	.065	.100**	.154	.065	.091*	.161	.065	.095*
Recommendation novelty				.059	.035	.052	.070	.036	.062	.062	.035	.055
Trust in AI				.200	.050	.225***	.207	.050	.233***	.200	.050	.225***
Distrust in AI				.050	.039	.051	.053	.039	.054	.052	.039	.053
Liking AI				-.021	.054	-.020	-.026	.054	-.025	-.021	.054	-.020
Platform attachment X Recommendation accuracy							.077	.037	.069*			
Content attachment X Recommendation accuracy										.057	.038	.048
Internal locus of control X Trust in AI												
Internal locus of control X Distrust in AI												
R square			.150			.575			.579			.577
Adjusted R square			.134			.558			.561			.559

(Continued)

Table 1. (Continued).

	Model 5			Model 6		
	B	SE	β	B	SE	β
Constant	3.641***	.121		3.633***	.121	
Age	-.005	.002	-.061	-.005	.002	-.063*
Male	-.036	.06	-.019	-.037	.060	-.019
Less than high school	-1.098	.469	-.073*	-.960	.473	-.064*
High school	-.171	.094	-.068	-.165	.094	-.065
College	-.125	.069	-.065	-.129	.069	-.067
African American	.029	.079	.012	.026	.079	.011
Asian	.055	.147	.012	.060	.146	.013
Hispanic	-.095	.137	-.022	-.084	.136	-.019
Multiracial	.031	.267	.004	.072	.266	.008
Platform attachment	.162	.050	.172**	.159	.050	.170**
Content attachment	.072	.049	.073	.083	.048	.085
Internal locus of control	-.017	.065	-.009	-.006	.065	-.003
Recommendation accuracy	.463	.054	.350***	.458	.054	.345***
Recommendation diversity	.171	.065	.101**	.165	.065	.097**
Recommendation novelty	.063	.035	.056	.055	.035	.049
Trust in AI	.198	.050	.223***	.184	.051	.207***
Distrust in AI	.056	.039	.057	.025	.042	.025
Liking AI	-.028	.054	-.027	-.028	.054	-.027
Platform attachment X Recommendation accuracy						
Content attachment X Recommendation accuracy						
Internal locus of control X Trust in AI	.090	.059	.050			
Internal locus of control X Distrust in AI				-.099	.061	-.056
R square			.577			.577
Adjusted R square			.559			.559

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(i.e., perceived accuracy, diversity, and novelty of recommendation algorithms), and heuristic processing variables (i.e., trust in AI, distrust in AI, and the liking of AI). This was the model before entering any interaction terms. Model 2 explained 55.8% of the variance in algorithm reliance (Adjusted $R^2 = 55.8$). Model 3 added the interaction term between platform attachment and the perceived accuracy of recommendation algorithms. Model 4 included the interaction effect between content attachment and the perceived accuracy of recommendation algorithms. Model 5 included the interaction effect between locus of control and trust in AI, whereas Model 6 included the interaction effect between internal locus of control and distrust in AI.

H1a proposed that platform attachment's positive association with algorithm reliance. The results of the OLS regressions showed that platform attachment ($\beta = .16, p < 0.01$) is positively associated with algorithm reliance, thus supporting H1a (See Model 2 in Table 1). In contrast, H1b, which proposed that content attachment is negatively associated with reliance on algorithm reliance, was not supported (see Model 2 in Table 1). H2 proposed that internal locus of control is negatively associated with algorithm reliance, and it was not supported (see Model 2 in Table 1).

Regarding *systematic* processing, H3a postulated a positive association between the perceived accuracy of recommendation algorithms and algorithm reliance. H3a was supported. As shown in Model 2 in Table 1, the results showed that perceived accuracy ($\beta = .34, p < 0.001$) is positively associated with algorithm reliance (see Model 2 in Table 1). H3b posited that the effect of perceived accuracy on algorithm reliance is weaker for those who have greater platform attachment. As seen in Model 3, Table 1, that interaction term was statistically significant ($\beta = .07, p < 0.01$), but the visualized plot showed that the effect of perceived accuracy was stronger for those who have greater platform attachment (see Figure 1). Thus, H3b was not supported. H3c proposed the stronger effect of the perceived accuracy of recommendation algorithms on algorithm reliance for those who have greater content attachment. That interaction term was not statistically significant, thus not supporting H3c. RQ1 asked about the relationship between the perceived diversity of recommendation algorithms and algorithm reliance. The OLS regression results showed that the perceived diversity of recommendation algorithms ($\beta = .10, p < 0.01$) is positively associated with algorithm reliance (see Model 2 in Table 1). RQ2 focused on the effect of the perceived novelty of recommendation algorithms on algorithm reliance. However, the effect of perceived novelty was not statistically significant.

Regarding *heuristic* processing, H4a proposed a positive effect of trust in AI on algorithm reliance. It was supported, and the results showed that

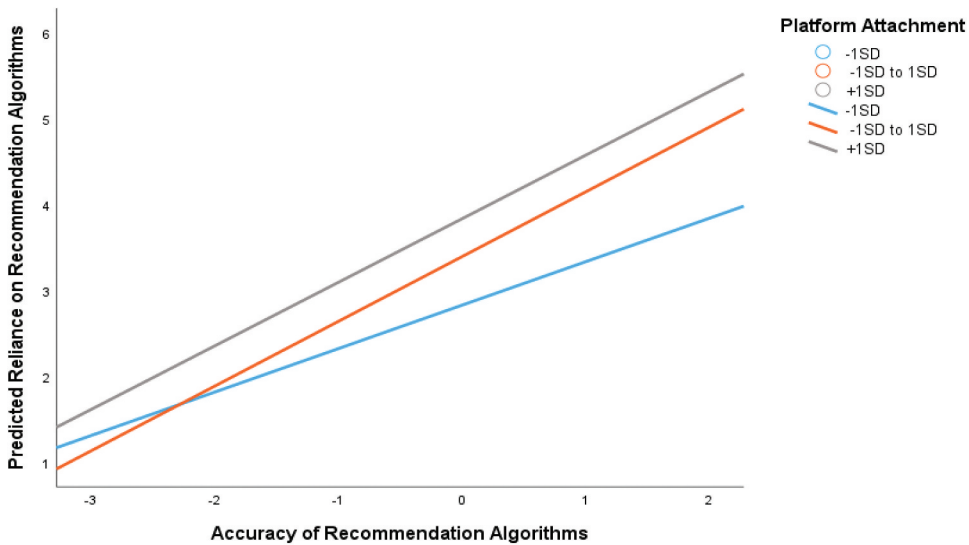


Figure 1. Interaction Effects between Platform Attachment and Perceived Accuracy of Algorithmic Recommendations on Algorithm Reliance.

trust in AI ($\beta = .23, p < 0.001$) is positively associated with algorithm reliance (see Model 2 in Table 1). H4b focused on the interaction effect between trust in AI and internal locus of control on algorithm reliance. It postulated that the effect of trust in AI on algorithm reliance is stronger for those with a greater internal locus of control. H4b was not supported; the interaction term was not statistically significant. H5a posited that distrust in AI is negatively associated with algorithm reliance. H5a was not supported because distrust in AI had no statistically significant effect. H5b proposed that distrust in AI has a stronger effect on algorithm reliance for those with a greater internal locus of control. H5b was not supported; the interaction term had no statistically significant effect. H6 proposed that the liking of AI positively affects algorithm reliance. The liking of AI had no statistically significant effect on algorithm reliance, thereby not supporting H6.

Discussion

This study sheds light on video streaming service users' underlying reasons behind their algorithm reliance via the lens of the heuristic-systematic model and the U&G perspective. In doing so, data were collected from U.S. Netflix users. This study chose Netflix because of its pioneering position in video streaming service and the prominent role of recommendation algorithms in its business model. The results show that Netflix users employ both systematic processing of recommendation algorithms and heuristic processing of AI in

determining how heavily they rely on recommendation algorithms and specifically that the perceived accuracy and diversity of recommendation algorithms and trust in AI do increase algorithm reliance. In addition, attachment to a video streaming platform increases algorithm reliance, and the perceived accuracy of recommendation algorithms has a stronger effect on algorithm reliance for those who have a greater attachment to that video streaming platform.

Theoretical implications

In terms of theory, this study enriches the literature on the behavioral use of recommendation algorithms in the context of entertainment-driven video streaming platforms. The extant studies on recommendation algorithms tended to focus on how recommendation algorithms affect satisfaction with various platforms, such as e-commerce or streaming platforms. However, little has been known on why some people use recommendation algorithms, while others barely use them. Unlike these prior studies, the present study recognized the importance of *reliance* on recommendation algorithms and centered on that aspect because recommendation algorithms are typically a default feature that is embedded in video streaming services, and users are thus *repeatedly* exposed to them. This study is indeed one of the first studies that elucidates that reliance on recommendation algorithms and reveals its antecedents. This current study also advances the literature on recommendation algorithms by digging deeper into the impacts of the *perceptions* of recommendation algorithms and AI on *behavioral* use. Most of the extant studies took computational or experimental approaches. Surprisingly scarce research has investigated how video streaming service users' perceptions of recommendation algorithms and AI influence their use of recommendation algorithms.

This study has found that Netflix users employ both systematic and heuristic processing in determining how heavily they rely on recommendation algorithms. Regarding systematic processing, both the perceived accuracy and the diversity of recommendation algorithms increase algorithm reliance; however, perceived novelty does not have such an impact. In particular, perceived accuracy has the strongest effect on algorithm reliance, which suggests that users do strive to rationally evaluate recommendation accuracy and will prioritize this *systematic* cue in determining algorithm reliance. The strongest impact of perceived accuracy underscores the power of this systematic cue as a central route, as opposed to peripheral routes, although ordinary users of video streaming services lack knowledge about the mechanics of recommendation algorithms.

Accuracy has been suggested as a quality measure for recommendation algorithms; however, most of the extant studies have employed computational

methods. Thus, little empirical research has yet examined the impact of users' *perception* of accuracy. Through the data collected from a survey of Netflix users, the present study demonstrates that users' *perceived* accuracy substantially influences how heavily they rely on recommendation algorithms. Prior studies have found a positive link between accuracy and satisfaction with recommendation algorithms (Kim et al., 2021) or the helpfulness of recommendation algorithms (Kwon et al., 2021). Apart from prior studies that focused on *affective* responses to recommendation algorithms, the present study further reveals the effect of *perceived* accuracy on the *behavioral use* of recommendation algorithms.

The perceived diversity of algorithmic recommendations is another *systematic* cue that influences algorithm reliance. That data supports the importance of the perceived diversity of algorithmic recommendations for boosting algorithm reliance, although its effect is less than that of perceived accuracy. Prior studies that took conceptual or computational approaches had mixed views about the diversity of algorithmic recommendations; some emphasized the importance of such diversity for mitigating the similarity hole generated by excessive accuracy in recommendation algorithms (Smyth & McClave, 2001), whereas others suggested striking a balance between accuracy and diversity because overly diverse recommendations diminishes accuracy (Zhou et al., 2010). Others found no impact of recommendation diversity on the satisfaction with recommendation algorithms (Kim et al., 2021).

In contrast, the present study found that Netflix users will seek out diverse recommendations from algorithms and that perceived diversity increases algorithm reliance. This result stresses the importance of the perceived diversity of videos recommended for each user as a critical construct *independent* of perceived accuracy in contributing to the behavioral use of and dependency on recommendation algorithms. Regarding novelty, this study found no significant impact on algorithm reliance. Although studies *conceptually* have suggested novelty as a possible value of recommendation algorithms (Abdollahpouri et al., 2021), its impact on algorithm reliance lacks enough empirical evidence.

Along with the aforementioned systematic cues, Netflix users also employ heuristic processing as well. The use of both heuristic and systematic processing is in line with the heuristic-systematic model of information processing and extends our knowledge of algorithm reliance in the context of video streaming services. Trust in AI is a *heuristic* that increases algorithm reliance. The more that Netflix users trust AI, the more heavily they will rely on recommendation algorithms. Trust in AI is the second strongest predictor of reliance on recommendation algorithms. Extant studies have tended to focus on only *performance* indicators (e.g., accuracy) of *recommendation algorithms* just per se in predicting the intention to use or affective responses to recommendation algorithms.

However, given the still unknown underlying mechanisms of recommendation algorithms, it remains challenging for users to accurately evaluate their quality. Therefore, users' trust in AI is activated as a mental shortcut that determines how heavily they will rely on recommendation algorithms. This finding suggests *source* trust is an important heuristic that determines the use of recommendation algorithms. Many users of video streaming services have limited knowledge about how recommendation algorithms work, but they are aware that recommendations are generated by AI rather than by humans. Therefore, their trust in AI in general, as opposed to recommendation algorithms, influences their algorithm reliance. This finding extends the importance of *source* trust as a heuristic to the behavioral use of recommendation algorithms.

This study focused on recommendation algorithms in the context of video streaming services, particularly Netflix, which is an entertainment rather than a news-driven platform. Trust has been a crucial construct in the context of news-related media; the results thus further suggest that trust plays an important role as a heuristic that mitigates the uncertainty of algorithmic recommendations and not just for news, but also for entertainment-driven media in the AI era where AI is being widely employed across various realms of media. Although cognitive attitude (i.e., trust in AI) increases algorithm reliance, affective (i.e., the liking) and negative cognitive (i.e., distrust) attitudes toward AI do not influence algorithm reliance. Given the *default* nature of recommendation algorithms found on Netflix, these do not exert strong effects as heuristics on algorithm reliance.

Another contribution of this study is that attachment to a video streaming platform as a *medium* influences the reliance on recommendation algorithms, indeed a novel finding. Prior studies have tended to focus on the attributes of recommendation algorithms only per se; they have neglected users' human agency, namely, motivational orientations toward a platform or content. The impact of attachment to a video streaming platform on algorithm reliance and its interaction effect with perceived accuracy on algorithm reliance are significant departures in this study from prior studies. The effect of platform attachment suggests that those who are more attached to a particular video streaming platform are more passive in *searching for* videos themselves due to their habitual use of a video streaming platform. Therefore, they will more heavily rely on recommendation algorithms. This finding is partly in line with the prior studies that have suggested a habitual use of television among audiences who were attached to television as a medium rather than to the use of content in the pre-streaming era (e.g., Rubin, 1979, 1984).

However, these findings of the present study do not mean that those with a greater attachment to a particular video streaming platform watch whatever content is given on that platform. The present study found that the effect of perceived accuracy on algorithm reliance depends on the level of attachment

to the medium. Interestingly, perceived accuracy has a stronger effect on algorithm reliance for those with a *greater attachment to the video streaming platform*. In the pre-streaming era, those audiences who were attached to television were ritualistic and habitual in their television consumption rather than being goal oriented; they were less active in searching for specific content that they wanted (Rubin, 1984; Rubin, 1983). Now, in the streaming era, users' video consumption and content selection are more nuanced than a ritualistic and instrumental dichotomy. The present study reveals that users with a greater attachment to a platform do not simply ritualistically consume any given content on that video streaming platform. They still care about the content they watch on the platform. These findings shed light on the change in audience characteristics, content selection behavior, and motivational orientations following the transition from the television era, when traditional television was the dominant way to watch video content, to today's streaming era.

Practical implications

From a practical standpoint, the findings of this study suggest that as Netflix users perceive algorithmic recommendations to be more accurate and diverse, they rely more heavily on recommendation algorithms. Also, note that they recognize and evaluate accuracy and diversity of algorithmic recommendations *distinctively*. Mixing videos that accurately reflect users' interests with diverse content can diminish both the perceived accuracy and diversity of algorithmic recommendations because diverse recommendations can lower the perceived accuracy of algorithmic recommendations, or accurate recommendations can lower the perceived diversity of algorithmic recommendations. Therefore, this study suggests that video streaming services create separate sections for accuracy and diversity and clearly label them to enhance the perceived accuracy and perceived diversity of algorithmic recommendations, respectively. The degree to which algorithmic recommendations fit individuals' preferences is the most important predictor of algorithm reliance. Video streaming services could also ask their users about changing preferences frequently and integrate those responses into algorithms because there is no one who better understands users' preferences than the users themselves. In terms of recommendation diversity, video streaming services can enhance diversity and not just by genres. Themes, ethnic and gender representations, popularity, country of origin, and viewpoints can be also taken into account by those services.

As video streaming services face stiff competition in the U.S., customer retention and brand loyalty have become more important than ever before. Those who are attached to a particular video streaming platform are likely to spend more time on that platform, stick with it, and be exposed to more

ads on the same platform. This study found that attachment to a particular video streaming platform increases reliance on its recommendation algorithms and that perceived accuracy will more strongly affect the reliance on recommendation algorithms for those with a greater attachment to a specific video streaming platform. This finding suggests that recommendations that are reflecting users' interests are particularly important for retaining users who are highly involved with a given platform. Thus, increasing the proportion of recommendations that accurately reflect those users' preferences can be a strategic move for video streaming services. Concurrently, this study also warns that overemphasizing accuracy can lead those highly involved users to experience a similarity hole, which can cause a more serious problem if these users are prone to watch a limited selection of genres, themes, or viewpoints, such as those that express violent, sexual, or extreme political news. To mitigate this risk, video streaming services should also nudge these users by providing diverse content recommendations, depending on the types of content they are consuming.

Netflix users partially use trust in AI as a mental shortcut for determining how heavily they rely on recommendation algorithms. Thus, video streaming services and other technology companies that develop and use AI should be more transparent about the mechanics of AI, data training, security, and privacy and educate users about those common tenets of AI to build greater trust toward AI in general to make users more likely to embrace recommendation algorithms.

Limitations and future research

This study enriches our understanding of algorithm reliance in the context of video streaming services. However, its limitations should also be noted. This study focused on Netflix recommendation algorithms, and the study used a convenience sample of U.S. Netflix users because of the lack of publicly available information about that specific population. Survey participants were recruited from Prolific, and the data from Prolific is known to have greater validity than the data from other survey panels (Douglas et al., 2023). Still, these results should not be generalized to apply to the population of Netflix and video streaming users in general. As the number of video streaming services increased over the past decade, some of them pursued differentiation and focus strategies. Netflix is geared toward the general population that seeks a variety of long-form entertainment content, whereas other video streaming platforms, such as Shudder and TikTok, offer a specific genre of video content or target a specific group of audiences. The factors that influence algorithm reliance may thus differ across various video streaming platforms. Future

research should thus collect data from other video streaming services with different content offerings and different target audiences.

This study found that trust in AI is an important heuristic that determines algorithm reliance. The impact of trust is noteworthy because prior studies tended to highlight the impact of trust in the context of news-related media (e.g., Heim & Chan-Olmsted, 2023), whereas this study focused on Netflix, an entertainment-driven video streaming platform. Recently, AI has been widely used for a variety of media products and services. Future studies could thus examine the impact of trust in AI on the use of various entertainment-driven media products and services.

This study found that liking AI does not influence reliance on recommendation algorithms. Focusing on automated systems, Merritt (2011) found that the liking of automated systems positively influences the reliance on them initially, but that effect subsides later. In contrast, trust in those system has no effect initially, but it tends to influence the reliance on them later. Netflix and its recommendation algorithms are no longer new to Netflix users, which might be a possible reason for why liking AI does not influence the reliance on Netflix recommendation algorithms. Future research should further investigate how the interplay between liking and trust changes in terms of changing time horizons. With respect to internal locus of control, this study did not find any impact on the reliance on recommendation algorithms. A possible reason is the default nature of recommendation algorithms that are embedded into video streaming services. Thus, recommendation algorithms differ from standalone AI applications that do require *active* adoption or reject decisions. It would be fruitful to examine such differences in terms of reliance. Some users of video streaming services may also use external audience and/or critics review websites such as Rotten Tomatoes and IMDB to reduce uncertainty about videos recommended by algorithms. Future studies should further investigate how such external validation through experts and peer audiences influences the choice of videos recommended by algorithms and its interaction with locus of control.

In the context of recommendation systems, the term accuracy has been widely used in the extant studies, which is attributable to humans' perceptions of AI as machines. Accuracy has been the core tenet of machines. However, the conceptual definitions of accuracy are not consensual. Some studies focus on *predicting accuracy* (e.g., Pu et al., 2011; Kim et al., 2021), whereas others focus on how *similarly* algorithmic recommendations fit users' preferences (e.g., Coppens et al., 2023). Studies on recommendation algorithms often use the terms similarity and accuracy interchangeably in that both content-based recommendations and collaborative filtering focus on how similar the algorithmic recommendations are to what users have previously watched and how to match a user's preferences with other users who have similar preferences, respectively (Bobadilla et al., 2013; Victor et al., 2011). Other studies have

defined recommendation accuracy as a system's ability to search for "good" content (e.g., Ekstrand et al., 2014). In the context of video streaming services and broader social media that offer both branded and user-generated content, the term accuracy can also mean how accurate *the information* recommended by algorithms to users is. Future studies should further explicate the term accuracy as well as other relevant constructs.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the author upon reasonable request.

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Appendix. Constructs and Measurement Items

Construct	Measurement items
Reliance on recommendation algorithms Cronbach's alpha = .944 M = 3.351 (SD = .957)	How much do you rely on recommendation algorithms to choose videos on Netflix? (1 = never rely, 5 = heavily rely) How important are recommendation algorithms when selecting videos on Netflix? (1 = not at all important, 5 = very important)
Platform attachment Cronbach's alpha = .911 M = 3.026 (SD = 1.013)	I would rather watch Netflix than do anything else. I would feel lost without Netflix. I could easily do without Netflix for several days.* Watching Netflix is one of the more important things I do each day. Netflix is very important in my life.
Content attachment Cronbach's alpha = .806 M = 2.910 (SD = 2.911)	I would rather watch my favorite television program than do anything else. I would feel lost without watching my favorite television program. ' I could easily do without watching my favorite television program for several days.* Watching my favorite television program is one of the more important things I do each day. My favorite television program is very important in my life.
Internal locus of control Cronbach's alpha = .875 M = 3.706 (SD = .504)	28 measurement items from Duttweiler (1984)
Perceived accuracy Cronbach's alpha = .944 M = 3.945 (SD = .719)	The videos recommended by Netflix algorithms match my interests.
Perceived diversity Cronbach's alpha = .820 M = 3.918 (SD = .562)	The videos recommended by Netflix algorithms fit my interests. The videos recommended by Netflix algorithms suit my interests. Netflix algorithms recommend videos for me based on diverse demographic representation.
Perceived novelty Cronbach's alpha = .657 M = 3.917 (SD = .845)	Netflix algorithms recommend videos for me based on various topics. Netflix algorithms recommend videos for me based on various themes. Netflix algorithms recommend videos for me based on various genres. Netflix algorithms recommend videos I do not expect. Netflix algorithms recommend videos I would not have thought to consider.
Trust in AI Cronbach's alpha = .924 M = 3.424 (SD = 1.072)	The videos recommended by Netflix algorithms are novel. I am confident in AI. AI provides security. AI has integrity. AI is dependable. AI is reliable. I can trust AI. I am familiar with AI.
Distrust in AI Cronbach's alpha = .895 M = 1.891 (SD = .970)	AI is deceptive. AI behaves in an underhanded manner. I am suspicious of AI's intent, action, or output. I am wary of AI. AI's action will have a harmful or injurious outcome.
Liking of AI Cronbach's alpha = .931 M = 4.121 (SD = .916)	I have strong negative emotions about AI.* I look forward to future AI developments. I am afraid of AI.* When I think about AI, I have mostly positive feelings.

* Reversely coded measurement items.