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RESEARCH ARTICLE

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Improving the effectiveness of personalized recommendations through attributional cues

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Abstract

Firms often employ personalized recommendations to help customers make purchase decisions. To improve the effectiveness of their personalized recommendations, some firms use cues to offer transparency on how they collect and use data to derive recommendations. We draw on attribution theory to propose an additional mechanism to improve the effectiveness of personalized recommendations with cues. Attributional cues, which refer to the underlying data (i.e., customers' own data vs. similar customers' data) used for personalized recommendations, aim to increase customers' self-attribution of personalized recommendations. Specifically, in three experimental studies, we show that attributional cues increase customers' self-attribution of personalized recommendations, leading to higher trust in and lower reactance to personalized recommendations. The accuracy and valence of the personalized recommendations moderate this attributional effect. As a result, employing attributional cues can be an essential and affordable tool for firms to increase the effectiveness of their personalized recommendations.

KEYWORDS

accuracy, attribution theory, attributional cues, personalization, personalized recommendations, reactance, trust, valence

1 | INTRODUCTION

In digital channels, personalized recommendations are omnipresent. According to a recent study, 71% of e-commerce sites offer personalized recommendations (Rigby & Jindal, 2019). Therefore, most people have likely encountered personalized recommendations such as “Top picks for you” (Amazon.com) or “More of what you like” (Spotify). These cues are prime examples of personalized recommendations, or suggestions for products and services that firms match with customers' preferences from their knowledge about those customers (Xiao & Benbasat, 2007). Yet some people may wonder why they are receiving such recommendations.

To address this question, firms often justify their approach by providing customers with additional information in the form of cues. Amazon, for example, declares “Customers who bought this item also bought…,” while Spotify states “Popular with listeners of….” To reduce customers' privacy concerns and increase their propensity to adopt personalized recommendations, some firms use cues to offer further transparency on how they collect and use data to derive personalized recommendations (Aguirre et al., 2015; Liao & Sundar, 2021). Research has mostly focused on this transparency offered by cues as the linking variable between the use of cues and an improved perception of personalized recommendations by customers (e.g., higher trust and purchase intention) (see Table 1).

TABLE 1 Overview of main empirical research on cues in the context of personalized recommendations and this study.

Studies	Cue referring to			Main underlying mechanism			Mediating and dependent variables	Moderating variables
	Method	Justification	Underlying data	Transparency	Relevance	Self-attribution		
Benbasat and Wang (2005)	x	x		x			Trust, perceived usefulness and ease of use, intention to adopt	
Dooms et al. (2015)	x	x		x			Transparency, control	
Gai and Klesse (2019)	x				x		Click-through intention	Consumption experience, product attractiveness, dissimilarity cue
Gedikli et al. (2014)	x	x		x			Satisfaction	
Gretzel and Fesenmaier (2006)			X		x		Perceived value and enjoyment of process, perceived fit of recommendations	
Liao and Sundar (2021)	x	x	X	x			Transparency, purchase intention, recommendation quality, trust	Product type, need for cognition
Martijn et al. (2022)		x		x			Preference, user interaction	Need for cognition, musical sophistication, openness
Nilashi et al. (2016)		x		x			Trust, purchase intention	
Senecal and Nantel (2004)	x			x			Product choice, credibility	Type of website, type of product
Tintarev and Masthoff (2012)		x			x		Effectiveness, satisfaction	
Wang and Benbasat (2007)	x	x		x			Trust	
Wang and Benbasat (2008)	x	x		x			Trust	
This study			X			x	Self-attribution, trust, reactance, purchase intention	Accuracy and valence of personalized recommendations

Note: The literature review is not intended to be exhaustive but rather includes recent and/or influential articles in each research field.

In addition to transparency, we propose a theoretically grounded mechanism to further improve the effectiveness of personalized recommendations with cues. Specifically, firms can use cues not only to provide transparency but also to influence customers' self-attribution of personalized recommendations. The idea of self-attribution originates from attribution theory, which explains that customers' causal attributions influence their perceptions of and reactions to different stimuli such as the outcome of tasks (Kelley, 1973) or the behavior of others (Kelley & Michela, 1980). That is, customers often make causal attributions about why they are receiving certain personalized recommendations. Self-attribution refers to the act of ascribing causes of events to oneself (Marsh et al., 1984). In our context, self-attribution means that customers attribute the cause of receiving personalized recommendations to themselves, which fosters acceptance. Self-attribution may thus help overcome the limitations of the currently implemented mechanisms of using cues to improve the effectiveness of personalized recommendations. We refer to cues that help increase customers' self-attribution as attributional cues.

Surprisingly, personalization research in general has barely discussed or employed attribution theory to assess the role of self-attribution. The few articles, which have drawn on attribution theory, do so to demonstrate that self-attribution of personalized dynamic pricing can increase price fairness perceptions (Priester et al., 2020; Schmidt et al., 2020). We argue that these results, however, cannot simply be transferred from one research field to the other for a number of reasons (see Section 2.3 for a more detailed discussion). A notable exception, examining personalized recommendations, is the study by Senecal and Nantel (2004), which draws on attribution theory to explain differences in trustworthiness of recommendation sources external to the customer (e.g., human experts, recommender systems, other customers). While this work provides valuable insights, it does not address sources internal to the customer, that is customers' self-attribution of personalized recommendations.

A potential reason for the neglect of attribution theory and the role of self-attribution in studies on personalization and personalized recommendations may lie in the focus of prior research on comparing the effectiveness of different types of cues about (1) the method used for deriving personalized recommendations; (2) a justification for showing personalized recommendations; or (3) the underlying data of personalized recommendations (see Table 1). At the same time, little is known about the underlying mechanism of these effects other than that they help increase transparency and, in some cases, the relevance of personalized recommendations.

For managers, understanding *how* to increase the effectiveness of personalized recommendations, however, is crucial as corresponding actions are often cost-intensive. This is especially relevant because firms already inadvertently use cues that function as attributional cues without, as of yet, considering their attributional effects. A better understanding of the effects of attributional cues, therefore, presents a potentially simple, cost-effective, and impactful way of increasing the effectiveness of personalized recommendations. Furthermore, personalized recommendations are not only one of the most common forms of personalization in the marketing mix (Mehmood et al., 2022), they are also similar to additional personalized elements of the marketing mix such as personalized advertising or personalized communications. Our findings on attributional cues are therefore likely also relevant for these personalized elements.

Across three experimental studies covering several product and service contexts, we explore the effects of attributional cues on the self-attribution of personalized recommendations. Mirroring the most common recommendation algorithms, our proposed attributional cues refer to the underlying data used for personalized recommendations (e.g., Amazon, Spotify, Netflix), either the customer's own data or the data of similar customers. In general, we evaluate the effectiveness of personalized recommendations in terms of customers' trust in and reactance to the recommendations. Furthermore, drawing on attribution theory, we consider the accuracy (i.e., how closely personalized recommendations match customer preferences) and valence (i.e., whether the content of personalized recommendations carries either a positive or negative meaning for the customer) of personalized recommendations as important moderators that may limit or increase the effectiveness of attributional cues. In an additional analysis, we evaluate customers' purchase intentions in response to personalized recommendations.

Overall, across our studies, we find that using attributional cues about the customer's own data increases the effectiveness of personalized recommendations over and above providing attributional cues about data of similar customers. As such, our work contributes to current research in several respects. First, by drawing on attribution theory, we provide an up-to-now-neglected, theoretically grounded mechanism of how the use of attributional cues improves the effectiveness of personalized recommendations by influencing self-attribution, trust in and reactance to the recommendations. Second, by assessing the role of self-attribution of personalized recommendations, we provide an additional explanation for why some personalized recommendations are more effective than others. Third, our results enrich the understanding of both personalized recommendations and attribution theory by showing that the accuracy and valence of personalized recommendations are important contingency factors for the effect of attributional cues.

Our findings provide managerial guidance on how to use attributional cues to improve the effectiveness of personalized recommendations. In our additional analyses, we find support that attributional cues increase purchase intention substantially and thereby have the potential to increase revenues with minimal investment from the firm. Importantly, our two moderating variables influence the effect of attributional cues; that is, attributional cues are especially effective when personalized recommendations are of low accuracy or a customer perceives a negative valence. Therefore, attributional cues may be especially useful in situations in which personalized recommendations are currently less effective.

2 | LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 | Personalized recommendations and customer responses

To provide personalized recommendations, firms first collect data to build customer profiles and to match products and services with these profiles (Li & Karahanna, 2015). These data include customers' transaction histories and personal, behavioral, and contextual information (Adomavicius & Tuzhilin, 2005). Firms then use these data for recommender systems with different matchmaking approaches (Alamdari et al., 2020). Among these, collaborative-based (i.e., matching on what similar customers like), content-based (i.e., matching on what the focal customer liked in the past), and hybrid (i.e., a combination of both) (Li & Karahanna, 2015) are the most common. In business practice, many firms increasingly rely on a hybrid approach to provide personalized recommendations to accurately fit customers' preferences (Gai & Klesse, 2019).

Research shows that customers respond to personalized recommendations in both favorable and unfavorable ways (Li & Karahanna, 2015). Favorable responses include perceived usefulness of the recommendations (Baier & Stüber, 2010), increased enjoyment (Benlian, 2015), enhanced decision quality and increased purchase intention (Alamdari et al., 2020). Unfavorable responses include privacy concerns, intrusiveness and perceived manipulation (Cloarec, 2020). Overall, personalized recommendations are only effective when customers adopt them (Xiao & Benbasat, 2007).

To boost the effectiveness of personalized recommendations, firms have worked to increase their accuracy (Bleier & Eisenbeiss, 2015). This is because low accuracy elicits fewer behavioral responses, such as click-through behavior (Bleier & Eisenbeiss, 2015), and might be perceived as annoying (Arora et al., 2008); by contrast, high accuracy can increase sales and loyalty (Alamdari et al., 2020). The provision of highly accurate personalized recommendations mostly depends on the availability and quality of data and the recommendation algorithms employed. High accuracy, however, also comes with some drawbacks, as it can engender reactance when customers feel concerned about their privacy (Bleier & Eisenbeiss, 2015). Personalization research describes this ambivalence of responses as the personalization paradox: "Greater personalization typically increases service relevance and customer adoption, but paradoxically, it also may increase customers' sense of vulnerability and lower adoption rates" (Aguirre et al., 2015, p. 34). To balance this paradox, firms need to find the right level of accuracy of personalization, be transparent about their data collection methods (Aguirre et al., 2015) and make sure that their personalization efforts benefit the customers (Cloarec et al., 2022). By increasing customers' trust in and reducing reactance to the recommendations, attributional cues could be a tool for firms to better balance the personalization paradox.

2.2 | Attribution theory

As mentioned before, attribution theory addresses individuals' need to construe causal explanations for why certain events happen. The theory suggests that individuals assess these causes along three dimensions (Weiner, 1986). The first dimension, the locus of the cause, refers to whether the cause is internal or external to the individual. A product breakdown, for example, may be attributed internally if the individual did not use the product as intended by the manufacturer. By contrast, the breakdown will be attributed externally if a defective product was sold by the manufacturer (Vaidyanathan & Aggarwal, 2003). The second dimension, stability of the cause, refers to whether the attributed cause is of temporal or persistent endurance. For example, an individual may perceive a stockout of a product as temporal if its shipment is delayed and as persistent if the product was eliminated from the manufacturer's product portfolio. The third dimension, controllability, refers to whether the cause is manageable or unmanageable for the individual (Weiner, 1986). An individual will perceive a cause as manageable if it was performed by willful choice and if other options were available (Vaidyanathan & Aggarwal, 2003).

After assessing locus, stability, and controllability, individuals form overall attributions of the cause and adjust their behavior to improve future outcomes (Kelley, 1973). Attributing the cause to themselves is referred to as self-attribution (Marsh et al., 1984). Thus, changing individuals' assessment of the causes along these dimensions (e.g., by providing additional information) can increase or decrease their self-attribution and, in turn, influence their behavior. Importantly, according to attribution theory, firms are capable of directing customers' causal attributions by changing, for instance, the type of cookie notices on websites (Schmidt et al., 2020).

2.3 | Self-attribution of personalized recommendations

Attribution theory provides a sound theoretical explanation for why some personalized recommendations are more effective than others. While attribution theory originated in psychology (Weiner, 1986), marketing scholars have frequently applied the theory to explain phenomena such as price fairness perceptions (e.g., Schmidt et al., 2020) and customers' preference construction (e.g., Yoon & Simonson, 2008).

With respect to research on the personalization of the marketing mix, attribution theory has rarely been discussed. Specifically, Schmidt et al. (2020) as well as Priester et al. (2020) draw on attribution theory to demonstrate that self-attribution of personalized dynamic pricing can increase price fairness perceptions. This work indicates that attributions strongly influence customer responses to personalization. We argue, however, that these research fields differ in key characteristics and therefore results cannot simply be transferred from personalized dynamic pricing to personalized recommendations. First, personalized dynamic pricing often results in relatively strong negative fairness perceptions (Priester et al., 2020), which probably does not hold true to such an extent for personalized recommendations. Second, personalized dynamic pricing typically takes place more covertly and therefore customers are less aware of it compared to personalized recommendations. Third, personalized dynamic pricing will likely be perceived as less intrusive than personalized recommendations as it does not appear to be based on the same type of customer data (e.g., customer preferences).

Surprisingly, research on personalized recommendations has barely drawn on attribution theory. This is astonishing because attribution theory is highly relevant in the context of personalized recommendations. Confronting personalized recommendations, for example, will trigger questions of “why” (i.e., the cause) the recommendations were received and “who” is responsible for them (i.e., locus and controllability) (Wang & Benbasat, 2007). As a result, the customer will assess the locus and controllability to attribute the cause of the personalized recommendations. In our research context, the proposed attributional cues relate to the source of data (customer's own data or other customers' data) but do not address a time aspect (e.g., when the data were collected). As such, they primarily influence the assessment of the locus and controllability, but not the stability of the cause. We therefore exclude stability from further discussion.

The locus of personalized recommendations can be both internal—the customer him- or herself feels responsible—or external—the firm is held responsible—to the individual. Meanwhile, the controllability of personalized recommendations can be high—the customer controls the content of the personalized recommendations—or low—the firm controls the content of the personalized recommendations. We propose that for personal recommendations, locus and controllability are correlated. That is, if the customer perceives the locus of the personalized recommendations to be more internal and their controllability to be high, the customer will attribute the personalized recommendations to him- or herself (i.e., increasing self-attribution).

2.4 | Attributional cues as antecedents to self-attribution

Antecedents influencing the attribution process can be broadly categorized into information, beliefs, and motivation (Kelley & Michela, 1980). In our study context, the provision of information as a firm's actionable instrument is most relevant. More concretely, we suggest that firms can use attributional cues about the underlying data (i.e., customer's own data and similar customers' data) to shift the locus of the personalized recommendations more toward internal while also increasing customers' perceived controllability.

For example, through attributional cues, firms can remind customers that they have shared their data with the firm and given consent for the use of these data in personalized recommendations. Consequently, customers should believe that they themselves have high controllability over the personalized recommendations (internal locus). As a result, such attributional cues should increase self-attribution of the personalized recommendations.

Conversely, an attributional cue about similar customers' data increases the self-attribution of the personalized recommendations to a lesser degree than an attributional cue about the customer's own data. This is because referring to “similar” customers implies that the customer is an integral part of the comparison, for which he or she has provided data. As such, compared with providing no attributional cue, the locus has moved somewhat towards internal and the perceived controllability has increased, but to a lesser degree than if the attributional cue referred only to the customer's own data. Thus, we propose:

H1. Providing an attributional cue about a customer's own data will increase the customer's self-attribution of the personalized recommendations more strongly than providing attributional cues about similar customers' data.

2.5 | Consequences of increased self-attribution

To understand how self-attribution influences customer responses, we focus on trust in and reactance to the personalized recommendations. In particular, we use trust in the personalized recommendations, an established success measure for personalized recommendations and frequently employed in personalization research, to capture favorable customer responses (Gorgoglione et al., 2019). Trust as the customers' belief that the personalized recommendations are benevolent, competent, and honest (Kim & Kim, 2011) constitutes a prerequisite for influencing the customers' behavior, as they will not adopt the recommendations otherwise (Komiak & Benbasat, 2006). A higher self-attribution might promote trust in at least two ways. First, the internal locus associated with high self-attribution implies that the customer assigns the responsibility for the personalized recommendations mostly to him- or herself, not to the firm. Trust in the personalized recommendations should therefore largely rely on the customer's trust in him- or herself. Because such trust is usually greater than any trust in the firm, trust in the recommendation should increase with an internal locus of self-attribution. Second, a high level of perceived controllability increases a customer's trust (Kim & Kim, 2011). As self-attribution is associated with a high level of controllability, it should therefore promote trust. Overall, providing attributional cues to customers helps them to better understand why personalized recommendations are displayed, which, in turn, also increases their trustworthiness (Adomavicius & Tuzhilin, 2005; Wang & Benbasat, 2007).

In addition, we consider reactance to be an established concept to capture unfavorable responses to personalized recommendations (Fitzsimons & Lehmann, 2004). Reactance to personalized recommendations may constitute a negative side-effect of highly accurate recommendations (Bleier & Eisenbeiss, 2015) and is thus an integral element of the personalization paradox (Aguirre et al., 2015). As noted previously, with personalized recommendations, firms aim to match customers' preferences with high accuracy (Alamdari et al., 2020). However, increasing the accuracy of these recommendations comes with the risk of customers' perceived loss of control and free choice over how their data are handled. Thus, the higher the accuracy of personalized recommendations, the higher customers' privacy concerns, as they may feel observed by the firm (Bleier & Eisenbeiss, 2015). Furthermore, recommending certain products can result in customers feeling intruded upon in their product choice process (Fitzsimons & Lehmann, 2004). In response, they may exhibit reactance as they try to maintain control over their choices (Brehm & Brehm, 1981). That is, they may act opposite to the personalized recommendations (Fitzsimons & Lehmann, 2004) by, for example, choosing an option that was not recommended. Ultimately, provoking reactance to the personalized recommendations limits their benefits for both customers and the firm (Aljukhadar et al., 2017).

Increasing the perceived control of customers over personalized recommendations presents a viable path for reducing reactance to personalized recommendations. When customers feel that they—and not the firm—can control and influence the content of the personalized recommendations, they should not consider them as an intrusion in their product choice process, but rather as an element of their own choice process. Because higher self-attribution is associated with controllability of the personalized recommendations, it should increase the perceived control of customers over personalized recommendations. Therefore, higher self-attribution may be a remedy that reduces reactance to recommendations and might help to address the personalization paradox. Thus, we propose:

H2. A customer's increased self-attribution will increase his or her trust in the personalized recommendations.

H3. A customer's increased self-attribution will decrease his or her reactance to the personalized recommendations.

2.6 | The moderating effects of accuracy and valence of personalized recommendations

We investigate two important moderators that may influence the effect of attributional cues on self-attribution: accuracy and valence of personalized recommendations. Both are theoretically grounded in attribution theory as they address the underlying mental processes and motivations individuals use to form self-attributions (e.g., Bradley, 1978; Kelley & Michela, 1980). They also carry high managerial relevance, as they lie within the control of the firm.

2.6.1 | Accuracy of the personalized recommendations

The accuracy of personalized recommendations is a key determinant of how customers respond to these recommendations (i.e., reactance) (Bleier & Eisenbeiss, 2015). It also influences the effect of attributional cues on self-attribution. Individuals are more likely to attribute expected (i.e., personalized recommendations matching their preferences) than unexpected (i.e., personalized recommendations not matching their preferences) outcomes to themselves (Bradley, 1978). Similarly, in the attribution process, customers search for similarities between the outcome (i.e., personalized recommendation) and the cause (i.e., customer preferences). Highly accurate personalized recommendations more closely resemble their preferences and thereby provide a strong starting point for them to assign the locus internally. Personalized recommendations of low accuracy do not resemble their preferences, and therefore customers assign the locus externally. As such, they will more easily attribute personalized recommendations of high (vs. low) accuracy to themselves (Kelley & Michela, 1980).

Thus, in situations of low accuracy of personalized recommendations (i.e., external locus), an attributional cue about a customer's own data complements the attribution process. It shifts the locus and controllability of the personalized recommendations to the customer and thus increases the self-attribution of the personalized recommendations. In situations of high accuracy (i.e., internal locus), an attributional cue about a customer's own data acts in a substitutive way. In such cases, the customer's self-attribution is already high and cannot be further reinforced by an attributional cue. Thus, we propose:

H4. The effect of an attributional cue about a customer's own data on self-attribution is stronger for personalized recommendations of low accuracy than for personalized recommendations of high accuracy.

2.6.2 | Valence of the personalized recommendations

The valence of personalized recommendations refers to their content and shows either a positive or a negative manifestation. A positive valence implies a favorable meaning for the individual (e.g., a book on art, which most customers will associate with a positive meaning for themselves such as sophistication), while a negative valence implies an unfavorable meaning (e.g., a book on weight loss, which most customers will associate with a negative meaning for themselves, such as being overweight) (Hess et al., 2020).

The valence of personalized recommendations influences the effect of attributional cues on self-attribution through the self-serving bias. According to this bias, people are inclined to attribute positive outcomes to themselves (i.e., assign an internal locus and high controllability) and negative outcomes to outside reasons (i.e., assign an external locus and low controllability) (Bradley, 1978). This self-serving bias is driven by their motivation for self-protection (Kelley & Michela, 1980). In other words, positive outcomes elicit higher self-attribution than negative outcomes.

The self-serving bias supports our argument that in situations of a negative valence of personalized recommendations (i.e., external locus), an attributional cue about a customer's own data complements the attribution process. In such situations, the attributional cue counteracts the low self-attribution of the negative valence of the personalized recommendation, as it shifts the locus and controllability of the recommendations to the customer. Thus, an attributional cue is especially valuable for personalized recommendations with a negative valence.

By contrast, in situations of a positive valence of the personalized recommendations (i.e., internal locus), an attributional cue about a customer's own data acts in a substitutive way. Here, the customer's self-attribution of the personalized recommendation is already high and cannot be further reinforced by an attributional cue. Thus, we propose:

> **H5.** The effect of an attributional cue about a customer's own data on self-attribution is stronger for personalized recommendations with negative valence than for personalized recommendations with positive valence.

Figure 1 summarizes our research framework. In addition to the outlined hypotheses, we consider purchase intention a key indicator of the effectiveness of personalized recommendations. Therefore, in our additional analyses, we test the direct effects of self-attribution as well as the indirect effects via trust in and reactance to personalized recommendations on purchase intention (see Section 6.1 for the results).

3 | STUDY 1

3.1 | Experimental design and procedure

Study 1 was a scenario-based online experiment, in which participants received personalized recommendations for a tablet. We chose tablets as the focal product category because customers often buy them online (Sellerapp, 2023) and are likely to rely on personalized recommendations (Balan U & Mathew, 2021). In line with prior research on personalized recommendations (e.g., Aljukhadar et al., 2017), employing a scenario-based experiment allows us to effectively vary the independent variable (i.e., provision of attributional cues) in a controlled way (Koschate-Fischer & Schandelmeier, 2014).

Specifically, the scenario informed participants that they planned to purchase a tablet and visited the website of a well-known online retailer from which they had frequently purchased before. Afterward, they received personalized recommendations from this online retailer for three tablets. The recommendations were accompanied by three conditions of attributional cues, to which we randomly allocated participants: (1) no attributional cue, (2) an attributional cue about the customer's own data ("Our personal recommendations are based on your last purchases and your account information"), or (3) an attributional cue about similar customers' data ("Our personal recommendations are based on the purchases of customers similar to you") (see Figure 2). While both attributional cues offered information about the underlying data, they focused on different data sources (the customer him- or herself vs. similar customers). The participants then answered a questionnaire that included manipulation checks and measures of the dependent and control variables. In line with methodological recommendations (Vomberg & Klarmann, 2022), we pretested the experimental procedure and questionnaire with 26 participants to ensure clarity. We adapted the experimental scenarios and questionnaire based on their feedback.

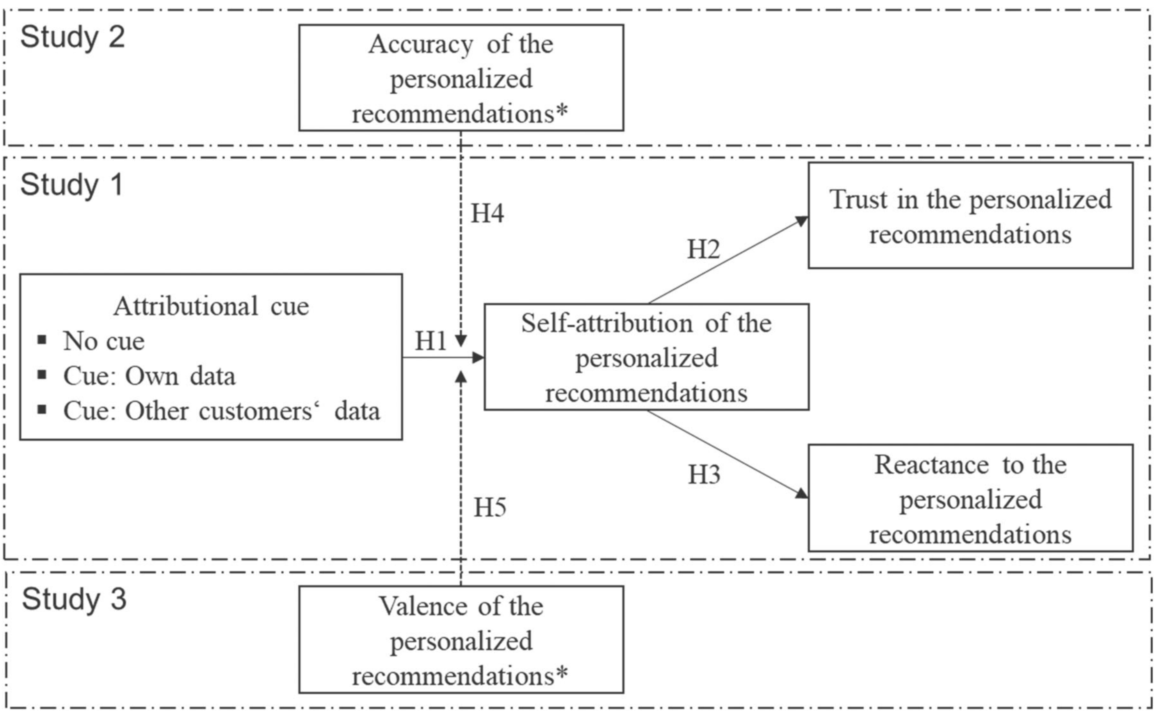

FIGURE 1 Research framework.

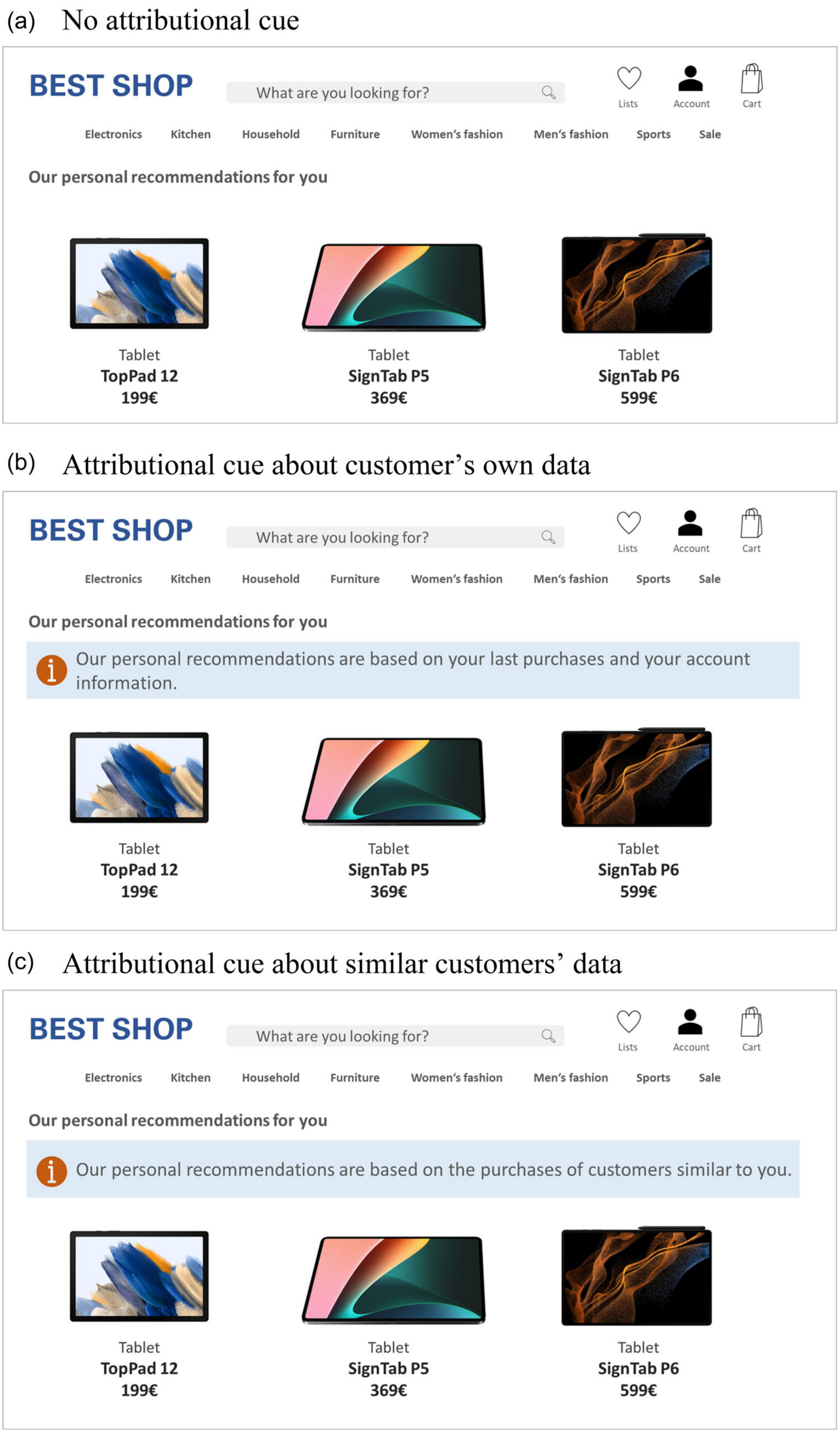

FIGURE 2 Experimental conditions varying in attributional cues (translated) (Study 1). (a) No attributional cue, (b) attributional cue about customer's own data, (c) attributional cue about similar customers' data.

3.2 | Sample

The online survey was completed by 330 European consumers from an online panel. After we excluded participants who failed to correctly notice the product category in the experiment, 296 participants remained in the final sample (Mode_{age} = 35–44 years, 51.0% female).

3.3 | Manipulation checks

A manipulation check assessed the perception of the attributional cues on a three-item 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Participants in the condition with the attributional cue about their own data perceived their personalized recommendations to be significantly more strongly based on their own data than participants in the other conditions ($\Delta M = 1.88$, $t = 8.88$, $p < 0.001$). Participants in the condition with the attributional cue about similar customers' data perceived the personalized recommendations to be significantly more strongly based on similar customer data ($\Delta M = 1.42$, $t = 6.31$, $p < 0.001$). Therefore, we deemed the intended manipulation of attributional cues successful.

3.4 | Measures

We measured self-attribution with a three-item 7-point Likert scale (1 = *not at all*, 7 = *very much*) adapted from Yalcin et al. (2022). We adapted the measure for trust in personalized recommendations from Grewal et al. (2004) and for reactance to personalized recommendations from De Keyzer et al. (2021). Following Brough et al. (2022), we used a single item ("How interested would you be in purchasing one of these products?") on a sliding scale from 0 (=*not at all*) to 100 (=*extremely*) to measure purchase intention for our additional analyses. Table 2 provides a full list of all measures used in the three studies.

3.5 | Results

To test H1, which posits an effect of attributional cues on self-attribution, we conducted a between-subjects one-factorial ANOVA, which revealed a significant effect ($F(2, 293) = 13.991$, $p < 0.001$). In support of H1, self-attribution was higher in the condition with the attributional cue about a customer's own data ($M = 4.16$, SD = 1.69) than in the condition with the attributional cue about similar customers' data ($M = 3.48$, SD = 1.81) and the control condition providing no attributional cue ($M = 2.91$, SD = 1.51). A Bonferroni post hoc test indicated that the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about customer's own data (1.25, 95% CI [0.68, 1.82]) was statistically significant ($p < 0.001$) while the change in self-attribution from the no-attributional-cue condition to the condition with the

TABLE 2 Overview of constructs used in experimental studies.

Construct	Adapted from	Scale item	Study 1 (Study 2; Study 3) Cronbach's *α*	*M*	SD
Self-attribution	Yalcin et al. (2022)	To what extent do you feel this recommendation ...			
		... reflects something about yourself	*α* = 0.95 (0.87;0.91)	3.47 (3.31; 2.82)	1.82 (1.80; 1.76)
		... can be attributed to something about yourself		3.45 (3.31; 2.93)	1.85 (1.89; 1.78)
		...is due to your personal qualities or behavior		3.65 (3.50; 3.11)	1.84 (1.86; 1.90)
Trust	Grewal et al. (2004)	I trust this recommendation	*α* = 0.97 (0.94;0.95)	3.52 (3.33; 2.82)	1.75 (1.75; 1.70)
		I think this recommendation is reliable		3.58 (3.60; 3.10)	1.76 (1.76; 1.80)
		I think this recommendation is credible		3.69 (3.86; 3.26)	1.73 (1.78; 1.82)
Reactance	De Keyzer et al. (2021)	I want to resist the recommendation	*α* = 0.88 (0.80;0.85)	4.54 (4.29; 5.41)	1.76 (1.98; 1.89)
		I want to dismiss the content of this recommendation		4.11 (3.95; 5.31)	1.90 (2.05; 1.95)
		I want to avoid this kind of recommendation		4.32 (4.28; 5.48)	1.98 (2.01; 1.84)
Purchase intention	Brough et al. (2022)	How interested would you be in purchasing one of these recommended products?	-	41.03 (40.40; 15.52)	29.37 (30.19; 22.72)

attributional cue about similar customers' data (0.57, 95% CI [–0.01, 1.15]) was not.

To assess the effect of self-attribution on trust in and reactance to the personalized recommendations, we ran a regression analysis. In support of H2, trust in the personalized recommendations increased when self-attribution increased ($\beta = 0.54$, SE = 0.05; $t(294) = 11.42$, $p < 0.001$). Likewise, in support of H3, reactance to the personalized recommendations decreased when self-attribution increased ($\beta = -0.19$, SE = 0.06; $t(294) = -3.40$, $p < 0.01$).

3.6 | Discussion

Study 1 demonstrates that attributional cues about a customer's own data increase the self-attribution of personalized recommendations more strongly than attributional cues about similar customers' data. The results of the Bonferroni tests further show that only the attributional cues about the customer's own data significantly increase self-attribution, while the effect of the attributional cue about similar customers' data is not significant. These results lend support to our theoretical reasoning that providing an attributional cue about a customer's own data is most effective in increasing the customer's self-attribution of the personalized recommendations. We also find evidence for the effects of higher self-attribution on trust in and reactance to personalized recommendations.

4 | STUDY 2

4.1 | Experimental design and procedure

Study 2 was also a scenario-based online experiment. To test the moderation hypothesis (H4) of the accuracy of personalized recommendations, we employed a 3 (no attributional cue, attributional cue about a customer's own data, and attributional cue about similar customers' data) × 2 (accuracy: low vs. high) between-subjects factorial design. We chose vacations as the study's context because it allowed easy manipulation of the accuracy of the personalized recommendations through a (mis-)match between destinations. In addition, we aimed to generalize the results of Study 1 (search product) to a different context (experience service).

The scenario informed participants that they wanted to book an all-inclusive vacation in Greece and visited the website of an online travel agency from which they had booked various vacations before. Afterward, participants received personalized recommendations from this online travel agency for two vacation packages. We randomly allocated participants to one of the two accuracy (low vs. high) conditions. In the low-accuracy condition, the personalized recommendations did not match the preferences stated in the scenario, with vacation packages for travel to Dublin and Iceland recommended instead. In the high-accuracy condition, the personalized recommendations matched their preferences (i.e., an all-inclusive vacation to Greece). In addition, we randomly allocated participants to one of the same three conditions for attributional cues accompanying the personalized recommendations as in Study 1. Subsequently, participants answered a questionnaire about manipulation checks, dependent variables, and control variables.

4.2 | Sample

The online survey was completed by 416 European consumers from an online panel. The free online panel proposed including attention checks within the scales (e.g., “I have read the question carefully, so I choose ‘1 Not at all concerned’”). After we excluded participants who failed these attention checks, 343 participants remained in the final sample (Mode_{age} = 25–34 years, 62.7% female).

4.3 | Manipulation checks

A manipulation check assessed the perception of the attributional cues on a three-item 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Participants in the condition with the attributional cue about their own data perceived their personalized recommendations to be significantly more strongly based on their own data than participants in the other conditions ($\Delta M = 2.81$, $t = 13.92$, $p < 0.001$). Participants in the condition with the attributional cue about similar customers' data perceived the personalized recommendations to be significantly more strongly based on similar customers' data than participants in the other conditions ($\Delta M = 2.81$, $t = 14.27$, $p < 0.001$). Therefore, the intended manipulation of attributional cues was successful.

We measured the manipulation of the accuracy of personalized recommendations with four items adapted from Aguirre et al. (2015). Participants in the high-accuracy condition perceived the personalized recommendations to be significantly more accurate than participants in the low-accuracy condition ($\Delta M = 1.87$, $t = 13.42$, $p < 0.001$). These results reflect a successful manipulation of accuracy.

4.4 | Measures

We used the same measures as in Study 1 for self-attribution, trust in and reactance to the personalized recommendations, and purchase intention.

4.5 | Results

To explore the proposed moderating effect of the accuracy of the personalized recommendations on the impact of attributional cues on self-attribution, we ran a two-way ANOVA. We found a significant main effect of attributional cues on self-attribution ($F(2, 337) = 23.10$, $p < 0.001$). Bonferroni post hoc tests revealed that the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about a customer's own data (1.15, 95% CI [0.68, 1.62]) was statistically significant ($p < 0.001$) while the change from the no-attributional-cue condition to the condition with the attributional cue about similar customers' data was not significant (0.03, 95% CI [−0.45, 0.51]). We also found a significant main effect of the accuracy of the personalized recommendation on self-attribution. Self-attribution was significantly higher in the high-accuracy condition than in the low-accuracy condition ($F(1, 337) = 36.67$, $p < 0.001$).

Importantly, the results showed a significant interaction effect of the attributional cue and the accuracy of the personalized recommendations on self-attribution ($F(2, 337) = 3.46$, $p < 0.05$). This effect indicates that the impact of attributional cues varies across personalized recommendations with high versus low accuracy.

In support of H4, simple effects analysis (see Figure 3) revealed that the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about a customer's own data was greater for low-accuracy personalized recommendations (1.49, 95% CI [0.96, 2.01], $p < 0.001$) than for high-accuracy ones (0.67, 95% CI [0.11. 1.23], $p < 0.05$). The attributional cue about similar customers' data resulted in a nonsignificant change in self-attribution for low-accuracy personalized recommendations (0.39, 95% CI [−0.14, 0.92]) but a significant decrease for high-accuracy recommendations (0.59, 95% CI [0.01, 1.16], $p < 0.05$).

We further performed the same regression analysis as in Study 1 to assess the effect of self-attribution on trust in and reactance to the personalized recommendations. The results replicate the findings of Study 1 and provide further support for H2 and H3.

4.6 | Discussion

Study 2 shows that personalized recommendations of low (vs. high) accuracy result in lower self-attribution. Thus, this study demonstrates that the accuracy of personalized recommendations moderates the effect of attributional cues on self-attribution. The effect of an attributional cue about a customer's own data is stronger for personalized recommendations of low accuracy than for those of high accuracy.

Attributional cues can therefore increase the effectiveness of personalized recommendations of low accuracy with minimal effort. Increasing the effectiveness of these recommendations would otherwise require significant investments to enhance accuracy, making this finding highly relevant for firms. In addition, Study 2 replicates the findings of Study 1 in the experience service context of vacations.

5 | STUDY 3

5.1 | Experimental design and procedure

Study 3 was also a scenario-based online experiment. To test the moderating role of valence of personalized recommendations, we employed a 3 (no attributional cue, attributional cue about a customer's own data, and attributional cue about similar customers' data) × 2 (valence: negative vs. positive) between-subjects factorial design. We chose banking as a study context because most customer relationships are long and continuous (Michalski, 2004). This context also allowed for easy manipulation of valence by the type of product recommended.

The scenario informed participants that they logged in to the website of their bank to check their account balance. Afterward,

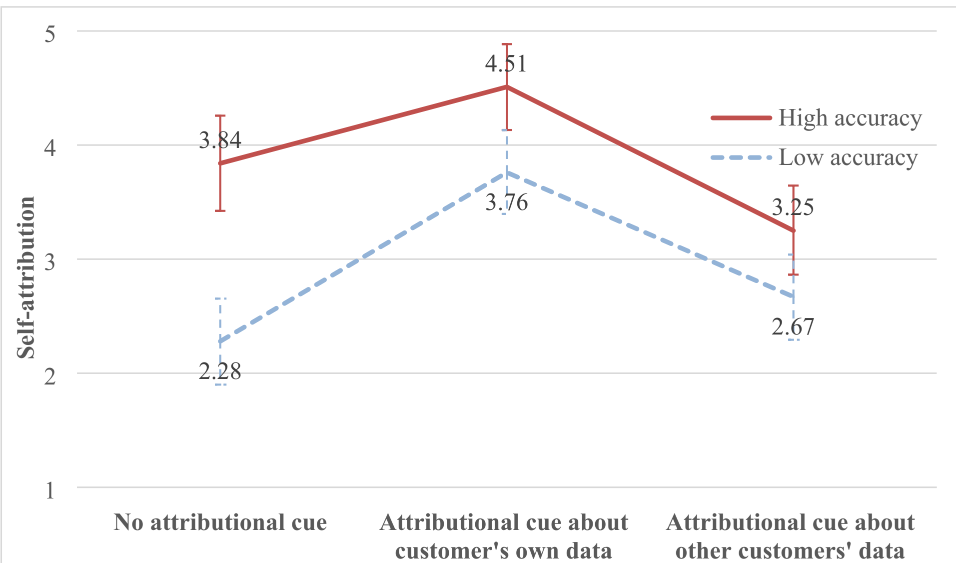

FIGURE 3 Simple effects analysis of Study 2 investigating accuracy as moderator. Error bars represent 95% CI of means. CI, confience interval.

participants received personalized recommendations from their bank for two financial products. We randomly allocated participants to one of the two valence conditions: (1) negative or (2) positive.

In the negative-valence condition, the recommendation was for products associated with financial stress, such as an installment purchase and account overdraft facility. In the positive-valence condition, the recommendation was for products associated with financial prosperity, such as a savings account and home savings. In addition, we allocated participants to one of the same three conditions of attributional cues accompanying the personalized recommendations as in Study 1. Subsequently, participants answered a questionnaire that measured manipulation checks, dependent variables, and control variables.

5.2 | Sample

In total, 530 European consumers from an online panel completed the online survey. After we excluded participants who stated that they do not use online banking or who failed attention checks similar to Study 2, 437 participants remained in the final sample ($Mode_{age}$ = 45-54 years, 56.8% female).

5.3 | Manipulation checks

A manipulation check assessed the perception of the attributional cues on a three-item 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Participants in the condition with the attributional cue about their own data perceived the personalized recommendations to be significantly more strongly based on their own data than participants in the other conditions ($\Delta M = 2.52$, $t = 13.77$, $p < 0.001$). Participants in the condition with the attributional cue about similar customers' data perceived the personalized recommendations to be significantly more strongly based on similar customers' data than participants in the other conditions ($\Delta M = 2.80$, $t = 14.71$, $p < 0.001$). Therefore, we consider the intended manipulation of attributional cues successful.

We manipulated the valence of personalized recommendations with two constructs (embarrassment and flattery), each on a three-item 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*) adapted from Hess et al. (2020) (embarrassment: $\alpha = 0.81$; flattery: $\alpha = 0.91$). Participants in the negative-valence condition perceived the personalized recommendations to be significantly more embarrassing than participants in the positive-valence condition ($\Delta M = 1.19$, $t = 7.49$, $p < 0.001$) and significantly less flattering ($\Delta M = 0.33$, $t = 2.78$, $p < 0.01$). Therefore, the manipulation of valence worked as intended.

5.4 | Measures

We used the same measures as in Studies 1 and 2 for self-attribution, trust in and reactance to the personalized recommendations and purchase intention.

5.5 | Results

To explore the proposed moderating effect of the valence of personalized recommendations on the impact of attributional cues on self-attribution, we ran a two-way ANOVA. Again, we found a significant main effect of attributional cues on self-attribution ($F(2, 431) = 16.16$, $p < 0.001$). Bonferroni post hoc tests revealed that the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about a customer's own data (1.03, 95% CI [0.59, 1.47]) was statistically significant ($p < 0.001$), as was the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about similar customers' data (0.48, 95% CI [0.02, 0.94], $p < 0.05$). We also found a significant main effect of valence on self-attribution. Self-attribution was significantly greater in the positive-valence condition than in the negative-valence condition ($F(1, 431) = 4.91$, $p < 0.05$). Finally, the results revealed a significant interaction effect of the attributional cue and the valence of the personalized recommendations on self-attribution ($F(2, 431) = 3.50$, $p < 0.05$). This finding indicates that personalized recommendations with positive and negative valence vary by the type of attributional cues employed.

In support of H5, simple effects analysis (see Figure 4) revealed that the increase in self-attribution from the no-attributional-cue condition to the condition with the attributional cue about a customer's own data was greater for personalized recommendations with negative valence (1.50, 95% CI [0.99, 2.01], $p < 0.001$) than for those with positive valence (0.57, 95% CI [0.07, 1.07], $p < 0.05$). The attributional cue about similar customers' data resulted in a nonsignificant change in self-attribution for personalized recommendations with positive valence (0.13, 95% CI [−0.39, 0.65]), but a significant increase for those with negative valence (0.83, 95% CI [0.29, 1.38], $p < 0.01$).

We again performed the same regression analysis as in Studies 1 and 2 to assess the effect of self-attribution on trust in and reactance to the personalized recommendations. The results replicate the findings of Studies 1 and 2 and provide further support for H2 and H3.

5.6 | Discussion

Study 3 shows that personalized recommendations with negative valence result in a lower self-attribution than those with positive valence. The findings show that the valence of the personalized recommendations moderates the effect of attributional cues on self-attribution. The effect of an attributional cue about customers' own data is stronger for personalized recommendations with negative valence.

Similar to Study 2, this finding indicates that attributional cues are especially useful in situations when the effectiveness of personalized recommendations is currently low due to a weak self-attribution. Consequently, firms can use attributional cues about customers' own data to increase the self-attribution of personalized

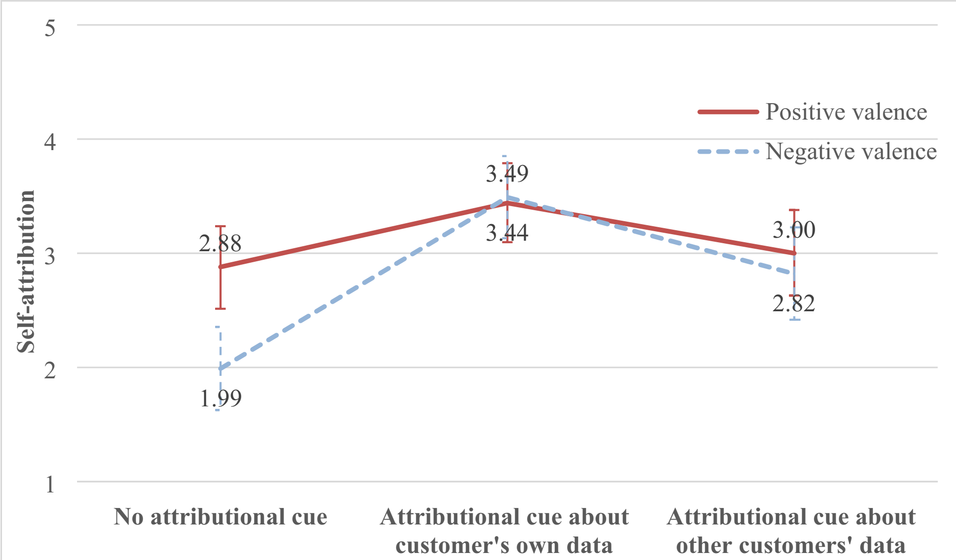

FIGURE 4 Simple effects analysis of Study 3 investigating valence as moderator. Error bars represent 95% CI of means. CI, confidence interval.

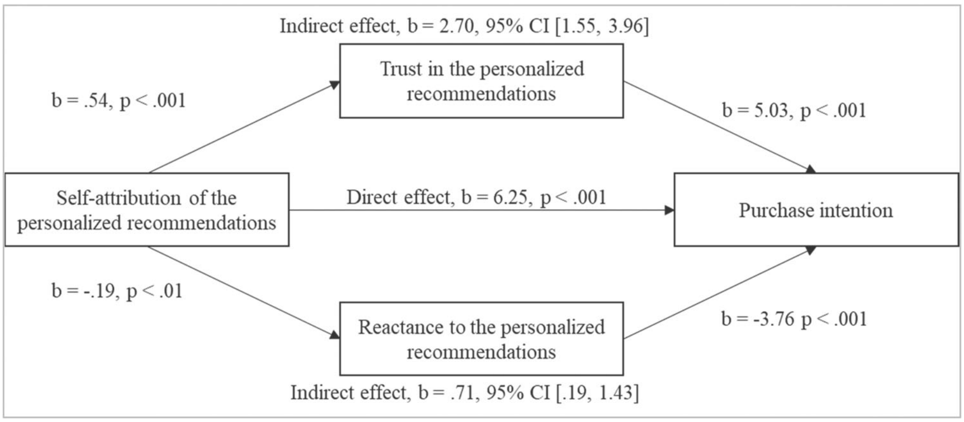

FIGURE 5 Relationship between trust in and reactance to the personalized recommendation and the effect of self-attribution on purchase intention (Study 1).

recommendations with negative valence and thus improve their effectiveness. Finally, Study 3 replicates the findings of Studies 1 and 2 in the context of banking.

6 | ADDITIONAL ANALYSES

6.1 | Results

Even though not hypothesized, we performed a mediation analysis with PROCESS model 4 (Hayes, 2022) (see Figure 5) to understand the relationship between trust in and reactance to the personalized recommendations and the effect of self-attribution on purchase intention. Please note that while we performed a mediation analysis, we cannot assume a causal relationship as we did not manipulate our mediators (Spencer et al., 2005). Instead, we use the results of the mediation analysis to better grasp correlational relationships between the variables. We found that both trust in and reactance to personalized recommendations are significantly correlated with self-attribution and purchase intention. At the same time, these correlational relationships do not fully explain the effect between self-attribution and purchase intention as both direct and indirect relationships were significant. That is, the indirect relationship between self-attribution and purchase intention through trust in the personalized recommendations ($\beta = 2.70$, 95% CI [1.55, 3.96]) and reactance to the personalized recommendations ($\beta = 0.71$, 95% CI [0.19, 1.43]) were significant as both confidence intervals did not include zero. The direct effect of self-attribution on purchase intention was also significant ($\beta = 6.25$, $p < 0.001$). In addition, we performed the same mediation analysis for Studies 2 and 3. The pattern of results is similar to the one for Study 1.

To measure the overall effect of an attributional cue about customer's own data on purchase intention, we also performed a mediation analysis with self-attribution of the personalized recommendation as the mediating variable. For this analysis, we also used PROCESS model 4 (Hayes, 2022). We found that only the indirect effect was significant ($\beta = 12.00$, 95% CI [7.14, 17.34]).

6.2 | Discussion

We show that firms can use attributional cues to increase purchase intention, increase trust, and reduce reactance to personalized recommendations, which partially explains the effect of self-attribution on purchase intention. Our findings also demonstrate that an attributional cue about customer's own data can increase a customer's purchase intention considerably (based on the 95% CI of the beta coefficient ranging from 7.14 to 17.34 percentage points). This result highlights the managerial relevance of attributional cues and indicates that it is worthwhile to assess the effect of an attributional cue about customer's own data on real purchase behavior in a field experiment.

7 | GENERAL DISCUSSION

Demonstrating the role of attributional cues for the effectiveness of personalized recommendations, our studies extend previous research by exploring the effects of self-attribution on trust in and reactance to personalized recommendations. The main findings of Study 1 show that attributional cues can affect self-attribution of personalized recommendations and, in turn, increase trust in and reduce reactance to the recommendations. We also demonstrate that this effect is stronger for personalized recommendations of low accuracy (Study 2) or negative valence (Study 3).

7.1 | Theoretical contributions

Our studies make several theoretical contributions. We extend existing research knowledge of customer responses to personalized recommendations by exploring attributional cues in the context of personalized recommendations (e.g., Gai & Klesse, 2019). Previous research has focused on using cues in general as a means of providing transparency on how the recommendations were derived (e.g., Liao & Sundar, 2021) and, in some cases, increasing the relevance of the personalized recommendations (e.g., Gretzel & Fesenmaier, 2006), but it has not tested how these cues potentially affect self-attribution. We demonstrate that cues can influence self-attribution of personal recommendations. Furthermore, we demonstrate that self-attribution increases trust in and decreases reactance to personalized recommendations and overall raises purchase intention. This finding reveals the relevance of attributional cues in improving the effectiveness of personalized recommendations. In addition, research on cues in the context of personalized recommendations has frequently considered their influence on trust but has not assessed their impact on reactance. We therefore find evidence that cues can reduce negative responses to personalized recommendations and thus present a potential tool to counterbalance the personalization paradox.

We also show that accuracy and valence of personalized recommendations moderate the effect of attributional cues and provide a theoretical explanation. This finding contributes to research on variables influencing the effectiveness of personalized recommendations (e.g., Baier & Stüber, 2010). Low-accuracy personalized recommendations increase the effect of an attributional cue about customer's own data because self-attribution of the recommendations by themselves is low. Similarly, negative-valence personalized recommendations increase the effect of an attributional cue about customer's own data because the self-attribution of the recommendations by themselves is low.

7.2 | Practical implications

We demonstrate that attributional cues are a powerful tool for managers to improve the effectiveness of personalized recommendations. This is especially relevant considering that firms undertake significant investments to provide customers with personalized recommendations, whose effectiveness is often limited. In such cases, attributional cues are a cost-effective solution.

Specifically, attributional cues can increase trust in and reduce reactance to personalized recommendations and, as our additional analyses show, result in higher purchase intention. In examining different types of attributional cues, we recommend that managers focus on highlighting customers' involvement in the personalized recommendations by providing data. We also show that attributional cues have an especially strong impact when personalized recommendations are normally of low effectiveness (low accuracy or negative valence). Furthermore, attributional cues about customer's own data have a positive impact for all assessed levels of accuracy and valence. These cues are therefore broadly applicable for personalized recommendations. This is particularly valuable as companies cannot accurately predict which personalized recommendations may be perceived as inaccurate or as having a negative valence.

Our findings also suggest that attributional cues can be a double-edged sword for customers. On the one hand, customers might benefit from increased trust in and reduced reactance to personalized recommendations, as these could reduce their mental load and increase purchase confidence. On the other hand, firms might apply attributional cues in a manipulative way and, for example, try to steer customers to choices that are less advantageous for them. This potential (mis-)use highlights the need for regulators to be aware of the effects of attributional cues in the purchasing process. Relatedly, firms might be limited in their use of attributional cues as they likely are legally required to only use cues that accurately reflect the nature of the personalized recommendations and are not outright misleading (i.e., claiming a personalized recommendation is based solely on past purchases when it is not).

7.3 | Limitations and further research directions

Our studies carry some limitations which provide opportunities for future research. While we paid attention to heterogeneity within our sample composition (e.g., age, gender), the studies used convenience samples. Thus, we cannot exclude that self-selection bias reduced the representativeness of our sample for the population of online shoppers. With regard to our mediation analysis, our findings remain correlational as we did not manipulate the mediating variables trust in and reactance to personalized recommendations. To confirm the causal relationships between the mediators and independent and dependent variables, future research may adapt a manipulation-of-mediator experimental design (Pirlott & MacKinnon, 2016).

Future research could extend the investigation to more personal product categories that reflect very intimate consumption behavior (e.g., consumption of alcohol, sexual preferences) to confirm whether the effect of self-attribution also exists under these conditions. Similarly, future studies could target other applications of personalized recommendations, such as social media or streaming services, or other personalized elements of the marketing mix, for example, personalized advertising. The study scenarios were set in the context of existing customer relationships in which customers might reasonably expect firms to know them. However, online customers often encounter personalized content outside existing customer relationships (e.g., advertising on third-party websites). Therefore, future research might explore whether attributional cues are also effective in those situations.

Future research should also investigate potential alternative explanations for self-attribution of low accuracy recommendations. For example, analyzing further variables that might act as competitive mediators would be a valuable route to further our understanding of the underlying process (e.g., Zhao et al., 2010). In addition, we examined the moderating effects of accuracy and valence separately. A fruitful way forward would incorporate testing whether low-accuracy personalized recommendations with negative valence also increase the effect of an attributional cue about customer's own data. If this holds true, attributional cues would also be useful for firms in situations where personalized recommendations are likely highly ineffective today as both low-accuracy personalized recommendations (Bleier & Eisenbeiss, 2015) and personalized recommendations with negative valence (Thomas et al., 2015) have been shown to be of low effectiveness independently of each other.

Beyond these extensions of our research and more generally, it might prove worthwhile for future research to assess the impact on self-attribution of various types of attributional cues (e.g., icons, showing customer names) and additional information (e.g., more details about the underlying data). As another avenue, research could give customers control over the personalized recommendations in addition to the attributional cue to strengthen the attributional effect. This could, for example, entail customers interacting with the personalized recommendations (i.e., similar to a chat bot) to add specific preferences or giving feedback on their personalized recommendations. In addition, assessing the effects of attributional cues in more detail by separately exploring changes in locus and control would be valuable. Research could also explore the effect of self-attribution on other customer responses to personalized recommendations, such as perceived usefulness and decision quality. Finally, while we find support for the hypothesis that attributional cues can increase self-attribution of personalized recommendations, there is likely a limit to this effect as the firm will always be held responsible to some extent for the personalized recommendation. Identifying where this limit is and how far firms can go in credibly increasing customer's self-attribution of personalized recommendations would therefore also be an interesting direction for future research.

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CONFLICTS OF INTEREST STATEMENT

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DATA AVAILABILITY STATEMENT

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

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