ONLINE FREE PRODUCT SAMPLING: THE RECIPROCITY AND DIAGNOSTICITY EFFECTS

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ABSTRACT

Product sampling is a popular product promotional strategy that emphasizes providing free product trials to new customers. This study aims to investigate the impact of different product sampling campaign characteristics (stimulus, i.e., free sample quantity, free sample diversity, and advertising information quality) on consumer cognitive and affective reactions (organism, i.e., perceived diagnosticity and perceived reciprocity) and consumer loyalty (response, i.e., product purchase intention and product rating). By collaborating with a leading Chinese beauty and care product sampling platform, we distributed the questionnaires to platform users who were actual free sample receivers and collected campaign information. Both subjective and objective data were collected to empirically test the research model. Our major findings suggest that perceived reciprocity has a positive and significant effect on product rating, but it does not affect consumer purchase intention. In contrast, perceived diagnosticity positively affects consumer purchase intention while it does not affect product rating. Research findings are discussed and are expected to enrich the product sampling-related literature and contribute to both academia and practice.

Keywords: Free product sampling; Product rating; Incentivized reviews; Reciprocity effect; Diagnosticity effect

1. Introduction

Product sampling refers to “offers of a free amount or a trial of a product for consumers” (Jain et al., 1995). It emphasizes providing free product trials to new customers. Product sampling, online or offline, has been a popular and effective product promotional strategy for attracting more product reviews (Lin et al., 2019; Pu et al., 2021) and increasing product sales (Zhang et al., 2018). The general process for free product sampling campaigns is similar across platforms. Potential consumers are invited to choose and receive free product samples, for which they are required to provide feedback.

Product sampling can take place in traditional offline places like supermarkets and stores, and it can be equally important in the online channel. Owing to the digital revolution, nowadays, an increasing number of brands leverage online digital channels to distribute their physical products through official websites or collaborate with third-party platforms. Recent reports show that consumers are apprehensive about going to crowded stores or shopping malls (Peekage, 2020). Instead, they tend to shop online. Hence, online product sampling provides a contactless way in which consumers can access their favorite products without setting foot in physical stores. Free product sampling not only can provide direct opportunities to consumers who desire to try the product, but it can also indirectly affect other

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consumers through a large number of generated online product sampling reviews (Lee & Tan, 2013). Online product sampling offers many advantages that offline product sampling cannot. First, it can accurately target intended consumers owing to the massive amount of consumer information collected (Pu et al., 2021). Second, online product sampling can generate larger and longer effects by indirectly attracting general consumers through online product sampling reviews (Yao et al., 2017). Many brands or platforms have adopted online free sampling as their primary product-promoting strategy, including Amazon Vine, Taobao, P&G, and so on. A recent report showed that within a population of targeted consumers, 97% of the consumers tried the free sample, and 14%–33% converted to the brand, showing a very high conversion rate compared to traditional promotional mechanisms (Taylor, 2020).

In the online free sampling context, extant studies have identified two major effects that affect consumer perceptions and behaviors: the reciprocity effect (Bawa & Shoemaker, 2004; Lin et al., 2019; Schumann et al., 2014) and the diagnosticity effect (or uncertainty-reduction effect) (Kempf & Smith, 1998; Pu et al., 2021). The reciprocity effect suggests that consumers may reciprocate the platform/brand by purchasing the product or giving a higher rating after they receive the free product (Gouldner, 1960). Perceived reciprocity is identified as an important factor that affects sample receivers' perceptions and decision processes (Bawa & Shoemaker, 2004; Lin et al., 2019). Perceived reciprocity is defined as "the extent to which consumers feel obligated to reciprocate another's action, not by directly rewarding his benefactor, but by benefiting another actor implicated in a social exchange situation with his benefactor and himself" (Ekeh, 1974). Meanwhile, perceived diagnosticity reflects the extent to which the product trial experience enables consumers to understand and evaluate product quality and performance (Jiang & Benbasat, 2004; Kempf & Smith, 1998). Consumers can better evaluate product quality and reduce product uncertainties by directly trialing the product through free product sampling campaigns (Pu et al., 2021), further facilitating their product purchase decision process.

Despite its importance, the empirical results of the effects of free product sampling are still mixed. First, empirical evidence of the reciprocity effect on product rating is inconsistent. Some literature has suggested that free product sampling increases product ratings because of the reciprocity effect (Cabral & Li, 2015; Lin et al., 2019; Qiao & Rui, 2022). However, other studies suggested that product sampling may not attract higher review ratings. A qualitative study, experimental study, and multilevel analysis of a field study dataset of more than 200,000 online reviews by product testers combined to reveal that product testing programs do not necessarily generate higher-quality reviews or better product ratings (Garnefeld et al., 2021). Given these inconsistent results, the impacts of the reciprocity effect in free sampling contexts need to be further explored. Second, previous literature concentrates on a single reciprocity effect which neglects the effect of uncertainty-reduction in the free product sampling context. Through free samples, consumers can learn more about product attributes and increase their knowledge and assessment of the focal product and even other nonsampled products that share common attributes with the focal product (Pu et al., 2021). Their study further revealed an increase in reviews' regular ratings due to the uncertainty-reduction effect instead of a reciprocity effect (Pu et al., 2021). The reciprocity and diagnosticity effects both matter in the free sampling context, whereas they may have different impacts on product ratings and consumer purchase intentions. It is important to take both two effects into consideration and empirically examine their different roles. Therefore, our first research objective is to investigate the different roles of the reciprocity and diagnosticity effects of free product sampling on consumer product rating and purchase intention.

Further, the existing literature mainly focuses on monadic product sampling strategies (single-product sampling situations), where product sampling is treated as a dummy variable (Lin et al., 2019; Lu et al., 2018; Mo & Li, 2018). However, there are, in fact, several different product sampling strategies marketers adopt. Product sampling campaigns vary in terms of the number of free samples and the diversity of free samples provided. Generally, there are two product sampling strategies that need to be decided in a free product sampling campaign. The first is the number/size of the same free product samples distributed in one sampling campaign (free sample quantity). Brands or platforms can choose only to give out a miniature version or a small portion of the product or to distribute the full-sized product. Bawa and Shoemaker (2004) investigated the impacts of free sample promotion on brand sales. They presented an extending model and suggested that if the free sample is a full-size package (i.e., a higher free sample quantity), consumers may have fewer opportunities to buy the product because they already have it and could consume it for a long time. Although providing a full-sized package reduces the level of incremental sales, it might increase consumers' purchase probabilities compared to a trial-size package. Though prior studies argued about the impacts of free sample quantity, they failed to provide clear empirical evidence. The second strategy is the product sample combination, that is, the number of different products distributed in one sampling campaign as a whole set of product samples (free sample diversity). Branders or platforms can choose between a monadic product sampling strategy or a simultaneous multiple sampling strategy. In monadic product sampling, consumers only evaluate one product sample in one product sampling campaign (Mazzucchelli & Guinard, 1999). In contrast, in simultaneous multiple product sampling, more than two different product samples are provided to consumers simultaneously (Mazzucchelli & Guinard, 1999).

Generally, all products included in simultaneous multiple sampling are complementary products (e.g., providing both shampoo and hair conditioner to one consumer in a product sampling campaign). The previous literature in the context of platform ecosystems has investigated a similar concept, product variety, which refers to the number of different digital product categories within a specific platform ecosystem (Boudreau, 2012). A high degree of product variety in a platform ecosystem could attract more users to the ecosystem. The product variety offered could also influence consumers' brand and product perceptions and choices (Berger et al., 2007). In free sampling contexts, teaming up different products and providing a joint product package helps brands or platforms save distribution costs, which also helps generate higher consumer reciprocity perception and motivates consumers to write more favorable reviews of the products. However, the advantages of free product sampling offer come at a price. Because products are offered for free, product sampling is also regarded as the most expensive product introduction and promotion strategy (Jain et al., 1995). Therefore, brands need to choose appropriate sampling strategies for their various products. Our second research objective is to investigate the effects of different product sampling campaign strategies, that is, free sample quantity and free sample diversity, on consumer product trial experience, including perceived diagnosticity and perceived reciprocity.

Finally, when a product sampling campaign starts, a sampling campaign advertising page with detailed product and brand description information should be provided to attract consumers' attention. The advertising information provides cues for consumers to evaluate product samples and form an ex-ante expectation, which may further affect their product perceptions and product evaluations. Therefore, advertising information quality plays an important role in free sampling campaigns. The third objective of this study is to investigate the impacts of campaign advertising information quality on consumer perceived diagnosticity and perceived reciprocity.

In collaboration with a leading beauty and care product sampling platform in China, we distributed a survey to real platform sample receivers and finally collected a total of 307 valid survey responses. We also collected objective sampling campaign data using a Python-based data crawler. Both subjective survey data and objective sampling campaign data are used to empirically test the research model. This study contributes to both academia and practice. Theoretically, this study explains and investigates the different effects of perceived reciprocity and perceived diagnosticity on purchase intention and product ratings. The results contribute to the literature on the effects of reciprocity and diagnosticity. Additionally, this study helps enrich and extend the product sampling literature by taking different product sampling characteristics into consideration. To the best of our knowledge, this study is the first to investigate the impacts of free sample quantity, free sample diversity, and campaign advertising information quality. The research results help to explain the different impacts of sampling characteristics on consumer purchase intention and product rating. For practitioners, product sampling comes at a price. It is important for brands and platforms to choose appropriate sampling strategies and wisely manage their product sampling campaigns. The research findings provide practical implications for how to choose appropriate product sampling strategies for various products and how to better manage product sampling campaign characteristics in promoting consumer product trial experience, increasing customer purchase intention, and attracting more favorable product ratings.

The rest of the paper is organized as follows. Section 2 discusses the related literature on product sampling, the norm of reciprocity, the diagnosticity judgment, customer loyalty, and the Stimulus-Organism-Response (S-O-R) framework. Section 3 provides the research model and hypotheses development. Section 4 introduces the research context and research methodology. Section 5 outlines the research results. Section 6 concludes with the key findings, theoretical contributions, and practical implications. Research limitations and future research directions are also discussed.

2. Literature Review

2.1 Related Literature on Product Sampling

Product sampling is a popular promotional strategy for new product introduction that provides a direct opportunity for consumers to try and experience products. The existing literature on free product sampling has mainly focused on two related perspectives: (1) the consumer perspective, which examines the impacts of free product sampling on consumer perceptions, and (2) the marketer perspective, which examines marketing outcomes, such as product sales and product review generation behaviors.

First, the existing literature has investigated the impacts of free product sampling on consumer perceptions, including product beliefs (Marks & Kamins, 1988), consumer brand perceived quality (Sprott & Shimp, 2004), and consumer product evaluation (Biswas et al., 2014). Existing empirical research has suggested that product sampling may lead to stronger belief and attitudinal confidence than advertising (Kempf, 1999; Marks & Kamins, 1988). Previous studies also examined the order effect on customer choice when multiple products are provided at the same time (Biswas et al., 2014; Mantonakis et al., 2009). Their results showed that consumers prefer the last product when sampling a sequence of products with dissimilar sensory cues (e.g., smell, taste, color, sound) (Biswas et al., 2014).

Additionally, the placement sequence of desirable and undesirable experiential products affects consumers' product preferences. Product sampling could also serve as a way to acquire product quality cues that reduce product uncertainty and allow consumers to assess preference fit, allowing consumers to make more informed purchase decisions (Hoang & Kauffman, 2018; Hu et al., 2010). Consumers who sample a product before buying it have a higher brand quality perception of that product compared with products whose brands did not offer product sampling (Sprott & Shimp, 2004).

Second, from the marketer perspective, the prior literature has investigated the impacts of free product sampling campaigns on product sales (Bawa & Shoemaker, 2004; Yao et al., 2017), sales of the sampled product's brand (Lu et al., 2018), consumers' future purchase probability (Heiman et al., 2001), product review ratings (Garnefeld et al., 2021; Lin et al., 2019; Mo & Li, 2018), review quality (Garnefeld et al., 2021), review quantity (Chen et al., 2017; Mo & Li, 2018), and so on. The research results span different types of products, including physical goods (Lin et al., 2019; Mo & Li, 2018) and information goods such as music (Wang & Zhang, 2009), content samples (Hoang & Kauffman, 2018; Li et al., 2019), and software (Lee & Tan, 2013).

Prior studies have extensively examined the impact of product sampling engagement on product review ratings. However, the results of these studies were mixed. Some studies found a positive effect of product sampling on subsequent review ratings. Lin et al. (2019) found that engaging in free product sampling could increase product ratings by 1.1% and that trial users are more likely to give a higher rating because of reciprocity. Pu et al. (2021) also found that after receiving free product samples from the Amazon Vine program, consumers' ratings for the purchased products increased by 2.25%. However, this rating increase was shown only after consumers received a sufficient number of free products. The review ratings were positively related to the number of free samples they received. At the same time, Mo and Li (2018) pointed out that free sampling decreases subsequent regular reviews ratings if a larger fraction of the reviews consist of free sampling reviews. Finally, Garnefeld et al. (2021) pointed out that only in certain circumstances (e.g., higher-priced products) does offering free product sampling help generate positive review ratings. Foubert and Gijsbrechts (2016) also found that free trials are a double-edged sword. The timing and consumers' usage intensity during the trial are key to the effectiveness of these promotions.

Previous literature has also investigated the effect of product sampling engagement on product sales. Consumer attitudes based on product trials were found to be a good indicator of product sales prediction (Smith & Swinyard, 1983). Bawa and Shoemaker (2004) found that engaging in free sampling can produce measurable long-term effects on sales that can be observed as much as 12 months after the promotion, whereas the effectiveness of free sampling varies between brands even in the same product category. Hoang and Kauffman (2018) investigated the effectiveness of the entertainment content sampling strategy used for on-demand series dramas. Their results showed that content sampling stimulates higher demand for series dramas.

Although product sampling strategy has long been investigated in the previous literature, and online platforms and brands widely apply various product sampling strategies, few studies have examined the effectiveness of different product sampling campaign characteristics. Further, the previous literature has mainly focused on monadic product sampling. To the best of our knowledge, there is no empirical study exploring the impact of free sample diversity, whether in offline or online contexts. This study differs from the previous literature by empirically investigating three important sampling characteristics: free sample quantity, free sample diversity, and advertising information quality. We also take a deeper look at how perceived reciprocity and perceived diagnosticity differently affect consumer purchase intention and product ratings.

2.2 Norm of Reciprocity

Perceived reciprocity is defined as "the extent to which consumers feel obligated to reciprocate another's action, not by directly rewarding his benefactor, but by benefiting another actor implicated in a social exchange situation with his benefactor and himself" (Ekeh, 1974). The norm of reciprocity routes in social exchange theory specifies that people should help those who have helped them by returning equivalent benefits (Kim et al., 2019). Reciprocity has two predictors: gratitude and obligation (Gouldner, 1960). Gratitude is defined as "the positive affective response to receiving a benefit or a favor" (Emmons & Crumpler, 2000). In contrast, obligation is a negative, unpleasant state caused by normative demands that can be perceived as aversive (Greenberg & Shapiro, 1971). Consumer's feelings of gratitude and obligation vary considerably from person to person. A consumer may feel obligated to purchase the product in return for a free trial because of compliance with social norms resulting from a state of obligation. However, the same purchase might be made out of a desire to express their gratitude rather than a sense of obligation.

The literature on social exchange has pointed out that there are two types of social exchange relationships: negotiated and reciprocal relations (Molm, 2003). Negotiated exchange contacts are built on bargained and binding agreements in which both parties agree on the terms of a specific, bilateral transaction. In contrast, reciprocal exchanges are non-negotiated and voluntary, with no set allocated arrangements in terms of what is exchanged or when the exchange should be completed (Molm, 2003). Reciprocity can be further divided into monetary-based reciprocity, which refers to "monetary benefits (e.g., provide digital coupons) prior to any subsequent request," and utility-based reciprocity, which refers to "functional context that is provided to users to improve their decision-making capacity" (Roethke et al., 2020). Monetary-based reciprocity is brands' or platforms' most widely adopted strategy in free product sampling campaigns.

The norm of reciprocity specifies that people should help those who have helped them by returning equivalent benefits. Generally, people reciprocate a favor for three reasons: first, people may conform to a universal norm that rewards those who have treated them nicely (Kim et al., 2018; Liu et al., 2019). This reciprocity norm has long been imprinted in social societies and embedded in civil laws (Gouldner, 1960). People have a natural desire to treat others well, pay back their debts, and return favors (Gouldner, 1960) according to equity theory (Garnefeld et al., 2021). Second, people choose to reciprocate as a way to send symbolic representations, for example, to express their emotional appreciation through gratitude (Kim et al., 2018; Liu et al., 2019). Third, reciprocating serves as a way to avoid psychological distress (Liu et al., 2019). When people are provided a free gift or a favor, they feel a sense of obligation to provide something in return (Kim et al., 2019). Failing to repay the favor may result in feelings of guilt (Dahl et al., 2005). According to cognitive dissonance theory, a person will suffer cognitive dissonance if a conduct violates a personal norm or value, and the person feels responsible for the violation (Festinger, 1957).

Reciprocity was found to be an important factor in various contexts in the IS literature, including knowledge-sharing (Wasko & Faraj, 2005), healthy behaviors (Liu et al., 2019; Väänänen et al., 2005), and organizational contexts (Settoon et al., 1996). In the knowledge-sharing context, prior research indicates a strong sense of reciprocity and fairness facilitates knowledge-sharing behaviors. Individuals who are guided by a norm of reciprocity will contribute more knowledge to the community (Wasko & Faraj, 2005). Reciprocity is also an important factor in the healthcare context, in which it is mostly viewed through the lens of social support (Liu et al., 2019). The effects of social support may depend on the perceived balance between giving and receiving support in one's relationships. Väänänen et al. (2005) investigated the long-term effects of perceived reciprocity in giving and receiving support on health status in intimate relationships. Their results showed that the support dynamics of intimate relationships are associated with general health status during a significant period of time. Settoon et al. (1996) found that different exchange relationships among employees, organizations and immediate supervisors have different impacts on employee behaviors with regard to organizational commitment, in-role behavior, and citizenship behavior.

2.3 The Diagnosticity Judgment

The diagnosticity judgment is a subjective assessment contingent on contextual and individual factors (Qahri-Saremi & Montazemi, 2022). A piece of information/object that one consumer perceives as diagnostic in one context may not be perceived as such by another consumer or may not be perceived as such in a different context. Perceived diagnosticity reflects an individual's level of diagnosticity judgment in product experience, it is defined as "the extent to which consumers believe the trial experience is helpful to evaluate products" (Jiang & Benbasat, 2004; Kempf & Smith, 1998). The perceived correlation between the information provided and the judgment task determines perceived diagnosticity. It is often operationalized as the helpfulness and usefulness of information for making a judgment in empirical studies (Gabisch & Gwebu, 2011; Kempf & Smith, 1998; Qiu et al., 2012). Higher perceived diagnosticity enables consumers to understand a product more thoroughly and improves their cognitive evaluations of the product.

Product sampling campaigns are often introduced to decrease product uncertainty and information asymmetry problems. Hong and Pavlou (2014) distinguished two types of product uncertainty: product quality uncertainty and product fit uncertainty. Product quality uncertainty is the consumer's difficulty in evaluating the objective quality of a product (Dimoka et al., 2012; Spiller & Belogolova, 2017), and product fit uncertainty is the degree to which a consumer cannot assess whether a product's attributes match their subjective preferences (Hong & Pavlou, 2014). Information asymmetry problems are serious concerns that often discourage customers from buying experience products, especially beauty and skin care products. Product sampling facilitates consumers' product learning by providing free trials of products and therefore reducing or even eliminating product fit uncertainty and product quality uncertainty.

Perceived diagnosticity helps consumers evaluate information's usefulness in making judgments and choices (Aboulnasr, 2006). Previous studies have shown that perceived diagnosticity can alleviate information asymmetry, increase consumers' product understanding, and help consumers understand product values, further reducing consumer perceived uncertainty and finally increasing consumer purchase intention and actual purchase (Pavlou et al., 2007). If customers perceive that product information is diagnostic, they would be certain about estimating product quality and more confident about their purchase decisions (Kempf & Smith, 1998). Yi et al. (2017) found that perceived diagnosticity of a search experience positively affects users' decision satisfaction. Diagnosticity of product attribute information also helps consumers confirm or disconfirm their prior held beliefs and expectations toward a product.

2.4 Customer Loyalty

Customer loyalty has long been regarded as a central concept in the marketing and IS literature, attracting significant attention (de Matos et al., 2020; Eid, 2011). Customer loyalty is defined as "a collection of attitudes aligned with a series of purchase behaviors that systematically favor one entity over competing entities" (Watson et al., 2015). Given its importance, the previous literature has identified different theoretical domains and measurements of customer loyalty.

Loyalty can first be regarded as purchase loyalty (Selnes, 1993), which entails repeated purchases that result from a conation or action orientation characterized by a "readiness to act" in favor of a specific entity (Oliver, 1999). Purchase intention reflects the possibility that consumers plan to buy or are willing to buy a specific product or service in the future (Wu et al., 2011). It is an important indicator of future purchases and is often used as a proxy for purchase loyalty (Chaudhuri & Holbrook, 2001). When consumer purchase intention is high, consumers are more likely to build a positive product or brand commitment that drives them to make an actual purchase (Fishbein & Ajzen, 1977).

Loyalty can also be viewed as attitudinal loyalty, which includes a degree of dispositional commitment in terms of the unique value associated with the brand (Chaudhuri & Holbrook, 2001), such as product ratings (Wasko & Faraj, 2005). Online reviews could help reveal product quality and reduce subsequent consumers' product fit uncertainty (Hong & Pavlou, 2014). According to the findings of Temkin Group, 77% of customers would recommend a brand to a friend after a single positive experience (Rioux, 2020). When consumers provide favorable product ratings and recommend the product to other consumers, it reflects high consumer loyalty. A higher product rating also reflects consumers' positive recognition of products, which helps increase their product purchase intention. Many studies have identified a positive relationship between product ratings and purchase intentions (Chu & Chen, 2019; Hsu & Lin, 2015; See-To & Ho, 2014). In this study, we focus on the impact of free product sampling on product rating (attitudinal loyalty) and purchase intention (purchase loyalty).

2.5 The S-O-R Framework

The S-O-R framework, grounded in environmental psychology (Mehrabian & Russell, 1974), is widely used in consumer behavior to help explain the effect of external features on consumers' purchase intention (Hu et al., 2016; Jiang et al., 2010), postadoption behaviors (Hsiao & Tang, 2021), and impulse buying (Parboteeah et al., 2009; Zheng et al., 2019). It is known for describing how environmental stimuli are translated into consumer behavioral responses, such as purchasing or not purchasing, through different mediating mechanisms (organism). The S-O-R framework is highly relevant to this free sampling context, and it provides many advantages: (i) it provides a concise and theoretically sound way for examining sampling characteristics as environmental stimuli, and (ii) it enables the examination of the role of consumer cognitive and affective reactions on consumer product ratings and purchase intentions.

The S-O-R framework includes three elements: stimulus, organism, and response. Stimulus (S) or environmental stimuli refers to "the external factor leading to change in an individual's internal state" (Hsiao & Tang, 2021). Organism (O) or intrinsic state refers to "the internal experiences of an individual's affective cognition, including cognitive reactions and affective reactions" (Zheng et al., 2019). The cognitive reaction refers to "the mental processes occurring in an individual's mind when he or she interacts with the stimulus" (Eroglu et al., 2001; Parboteeah et al., 2009), for example, how a consumer processes product/platform-related information. In contrast, the affective reaction captures individuals' feelings or emotional responses like enjoyment, pleasure, and happiness (Parboteeah et al., 2009). Response (R) is the consumer behavior outcome, which represents individuals' final actions in response to a specific stimulus (Hsiao & Tang, 2021). Examples are customers' loyalty outcomes like recommendation, search, and retention.

The existing literature has posited that the characteristics of platforms/websites (Parboteeah et al., 2009), products, vendors, technologies, and marketing features could be regarded as environmental stimuli that affect consumers' internal state, for example, cognitive/affective reactions (Parboteeah et al., 2009), perceived hedonic/utilitarian value (Zheng et al., 2019), positive/negative emotions; and their behavioral response, for example, purchase intention or behavior (Zheng et al., 2019).

3. Research Model and Hypothesis Development

Building on the S-O-R framework and the previous literature on free product sampling, we operationalize the external stimulus as free sample campaign characteristics, including free sample quantity, free sample diversity, and advertising information quality. We view perceived reciprocity (affective reaction) and perceived diagnosticity (cognitive reaction) as organism factors, and we operationalize the final responses as two types of customer loyalty behaviors, consumer product rating (attitudinal loyalty) and purchase intention (purchase loyalty). Figure 1 displays the proposed theoretical model.

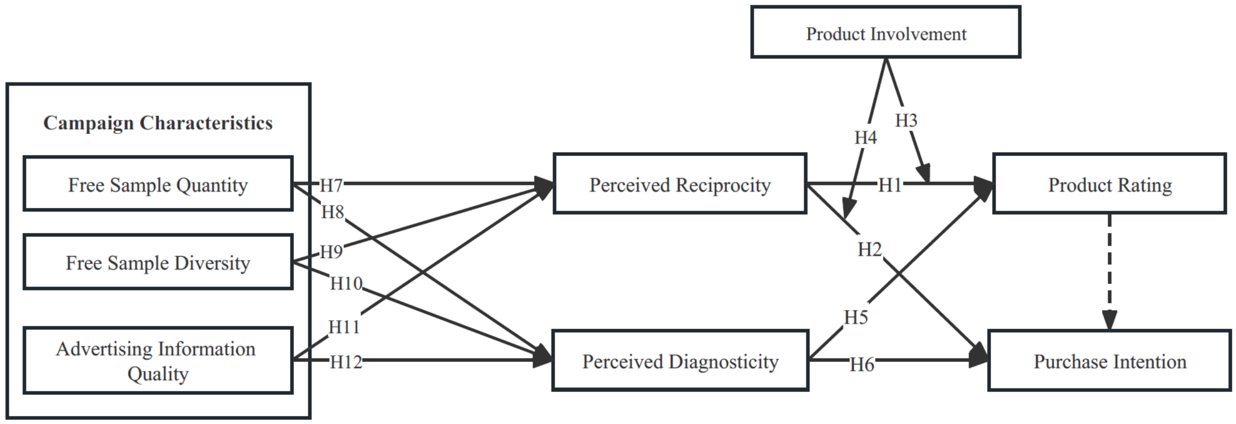

Figure 1: Research Model
(Note: The relationship in the dotted line is not the main focus of this study.)

3.1 The Reciprocity Effect from Free Product Sampling

In free product sampling, when consumers have a higher reciprocity perception, they face higher pressure to repay favors received from brands or platforms. Such reciprocity may result in them either giving higher ratings for products to show their thankfulness and gratitude or purchasing products in the future to repay their debt. The prior literature has shown that free product sampling has an acceleration effect on consumers' next purchase of the sampled product, and an expansion effect, in which free product sampling induces purchasing by attracting consumers who would not consider buying the product without a free sample (Bawa & Shoemaker, 2004). Lu et al. (2018) found that receiving a product sample could increase consumers' purchase probability by around 300%. Yao et al. (2017) found that online physical product sampling could increase product sales, and popular brands enjoyed larger sales boosts. Bawa and Shoemaker (2004) found that distributing free product samples could influence consumers' purchasing behavior for 12 months after the sampling promotion. Regarding product ratings, Lin et al. (2019) found that engaging in free product sampling could increase product ratings by 1.1%, and trial users are more likely to give a higher rating because of reciprocity. Therefore, we propose the following hypotheses:

Hypothesis 1: Consumer perceived reciprocity has a positive effect on product rating.

Hypothesis 2: Consumer perceived reciprocity has a positive effect on product purchase intention.

Product involvement is an important construct in advertising-response-related theory (Vakratsas & Ambler, 1999). It plays a significant role in explaining consumer decision-making and responses to advertising, product trials, and purchase decisions (Wang et al., 2016). Consumer product involvement is defined as "a person's perceived relevance of the product based on inherent needs, values, and interests" (Zaichkowsky, 1985). It originates from persuasive communication literature. Product involvement is a stable characteristic that does not change very much over time and varies between customers (Mittal & Lee, 1989). Findings from the prior literature seem to show that increased involvement results in more attentive processing, generating heightened cognitive responses and greater information search. For example, the level of product involvement was found to reflect a consumer's thoughtfulness and motivation for purchasing a product (Wang et al., 2016). Customers who are more involved in the product are more likely to seek out brand- and product-related information, to use greater criteria when making a purchase decision, and to form attitudes toward the product that is more resistant to change (Petty et al., 1981).

Because high and low product involvement consumers have been found to differ in many ways, product involvement is also expected to influence consumer reciprocal behaviors (Kolyesnikova et al., 2009). The effects of reciprocity can be further enhanced when loyalty program advantages are benevolently motivated, given freely, and offered when the consumer needs them the most (Palmatier et al., 2009). Similarly, the effects of reciprocity could be higher when product involvement is high. When product involvement is high, consumers' emotional appreciation towards the free sampling product is likely to be higher. Therefore, we propose that the effects of reciprocity can be enhanced when product involvement is high.

Hypothesis 3: The effect of perceived reciprocity on product rating will be stronger when product involvement is high.

Hypothesis 4: The effect of perceived reciprocity on purchase intention will be stronger when product involvement is high.

3.2 The Diagnosticity Effect from Free Product Sampling

The perceived diagnosticity helps consumers evaluate the information related to product features in making judgments and choices (Aboulnasr, 2006). Prior research has provided evidence of the effect of perceived attribute diagnosticity on consumers' evaluations, suggesting that the diagnosticity of product attributes helps consumers evaluate the quality and performance of a product (Jiang & Benbasat, 2004; Kempf & Smith, 1998). Perceived diagnosticity could also strengthen customers' confidence in their purchase decisions (Kempf & Smith, 1998). According to the integrated information response model, more reliable information obtained through free sampling results in higher-order cognition and a more favorable attitude toward purchase (Smith & Swinyard, 1982). Higher perceived diagnosticity enables consumers to understand the product more thoroughly and improves their cognitive evaluations of the product. If customers have a high perceived diagnosticity of the product, they are more certain about estimating product quality and more confident about their purchase decisions (Kempf & Smith, 1998). This helps increase their purchase intention.

When consumers have a high level of perceived diagnosticity, they can easily evaluate product attributes, evaluate product quality, and make product decisions. In contrast, when their perceived diagnosticity is low, consumers find it difficult to understand product quality and make product judgment decisions. Such consumers are more likely to provide lower product ratings because of their difficulties in understanding the advantages and disadvantages of the product. Therefore, we speculate that higher perceived diagnosticity may help generate higher product ratings. Overall, we propose the following hypotheses:

Hypothesis 5: Consumer perceived diagnosticity has a positive effect on product rating.

Hypothesis 6: Consumer perceived diagnosticity has a positive effect on product purchase intention.

3.3 Campaign Features as Antecedents of Reciprocity and Diagnosticity

The existing literature has suggested that product sampling could activate consumers' cognitive reaction to reciprocate the marker's favor (Garnefeld et al., 2021; Lin et al., 2019). Free product sampling helps consumers build a personal relationship with the product and the brand, providing a cost-free way for them to interact with the product. Receiving hassle-free products could make consumers happy, increasing their reciprocity perception, motivating them to write good reviews about the products, and providing higher product ratings. Prior research also found that distributing free product samples could evoke positive consumer sentiment and motivate higher product ratings (Kim et al., 2019; Lin et al., 2019; Pu et al., 2021).

In the free product sampling context, when the free sample quantity distributed to consumers is high, consumers may generate a high reciprocity perception. Additionally, compared with information goods with nearly zero marginal cost that can be easily distributed, physical products have relatively high marginal costs and need extra logistic efforts to deliver them to consumers. This helps generate a higher consumer perceived reciprocity and gratitude (Lu et al., 2018). Similarly, when free sample diversity is high, it means several different complementary products are given out to a consumer. Receiving free sample suites also helps increase consumer perceived reciprocity. Therefore, we propose that positive relationships exist among free sample quantity, free sample diversity, and consumer perceived reciprocity.

When a larger version of a product is provided in the sampling campaign, consumers can consume the product for a longer period. They can interact with the product for a longer period, which helps increase their understanding of the product's attributes and increase their perceived diagnosticity. If the quantity of the free product sample is insufficient, it is difficult for consumers to have an adequate understanding of the product and reduce their product uncertainty. Additionally, by providing a larger free sample package with higher diversity, two or more kinds of products are distributed to consumers at the same time, which may help them better evaluate the products' attributes. By consuming different products together, consumers may perceive that these products have better product performance. Therefore, we propose that positive relationships exist among free sample quantity, free sample diversity, and consumer perceived diagnosticity. Overall, we propose the following hypotheses:

Hypothesis 7: Free sample quantity has a positive effect on consumer perceived reciprocity.

Hypothesis 8: Free sample quantity has a positive effect on consumer perceived diagnosticity.

Hypothesis 9: Free sample diversity has a positive effect on consumer perceived reciprocity.

Hypothesis 10: Free sample diversity has a positive effect on consumer perceived diagnosticity.

When a product sampling campaign starts, an advertising page with detailed product and brand description information will be created to attract consumers' attention. Such advertising information provides cues for consumers to evaluate product samples. According to signaling theory, various observable attributes of an entity (i.e., extrinsic cues) can serve as quality signals (Michael, 1973). Signaling theory has been widely used to understand how consumers evaluate product quality when confronted with information asymmetries (Kirmani & Rao, 2000). When online consumers are confronted with information asymmetry in online free sampling campaigns, the advertising information quality of products influences consumers' perceptions of the products' quality by acting as a signal (Wells et al., 2011).

When the quality of advertising information is high, consumers will likely perceive the sampling campaign to have higher relevance, have higher product belief confidence, and recall more product selling points (Laczniak et al., 1999). When consumers have a higher perception of the relevance and importance of the sampling campaign, they are more likely to have a higher reciprocity perception. Further, a more well-informed consumer will pay more attention to the product and the sampling campaign details, helping increase their perceived diagnosticity. Therefore, we propose the following hypotheses:

Hypothesis 11: Advertising information quality has a positive effect on consumer perceived reciprocity.

Hypothesis 12: Advertising information quality has a positive effect on consumer perceived diagnosticity.

4. Research Methodology

4.1 Research Context

We collaborated with a leading Chinese beauty and care product sampling platform (Platform A, which has chosen to remain anonymous) to collect research data. Platform A is one of the leading online communities in China and features product composition querying and user-generated reviews for beauty and care products. The platform was set up in 2017 and had more than 30,000,000 users by March 2022. This platform enables different types of product sampling campaigns in which brands can decide the free sample quantity, free sample diversity, and campaign advertising contents (Figure 2). With the help of Platform A, we collected two types of data. The first set consisted of survey data from platform users who were actual free sample receivers. The second set consisted of objective sampling campaign data collected using the Python-based data crawler. All campaign-related information was collected. When filling out the questionnaire, respondents were asked to write their platform nickname and select the most recent free product sampling campaign they had engaged in, through which we connected the survey respondents to the campaign and matched the campaign and product-level objective data.

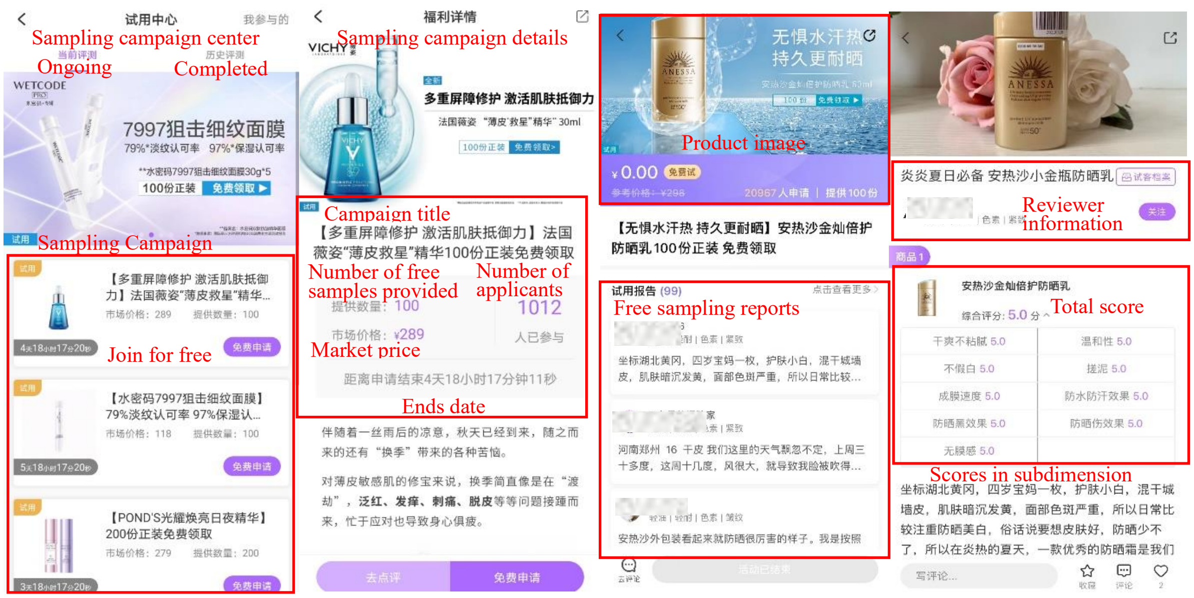

Figure 2: Platform Screenshots

The free product sampling campaigns are a featured function on this platform and have attracted numerous consumers. A typical online free product sampling campaign generally includes three stages, as Figure 3 shows: (1) The pretrial stage. During this stage, the platform posts free product sampling offers, displaying product pictures and information. Consumers who visit the platform and see the offer can apply for the free product sample before the offer expires. After the sampling campaign application stage ends, the platform selects a certain number of (depending on the number of free product samples the brand offers) successful free sample receivers from all campaign applicants. Those who are selected need to submit their address. The platform then sends out free product samples. (2) The product-trial stage. After receiving the free product sample(s), receivers can freely trial the product(s). They are required to submit a free sampling report during the given time points. (3) The post-trial stage. After receivers submit the sampling report, other consumers can browse and comment on these reports on the platform.

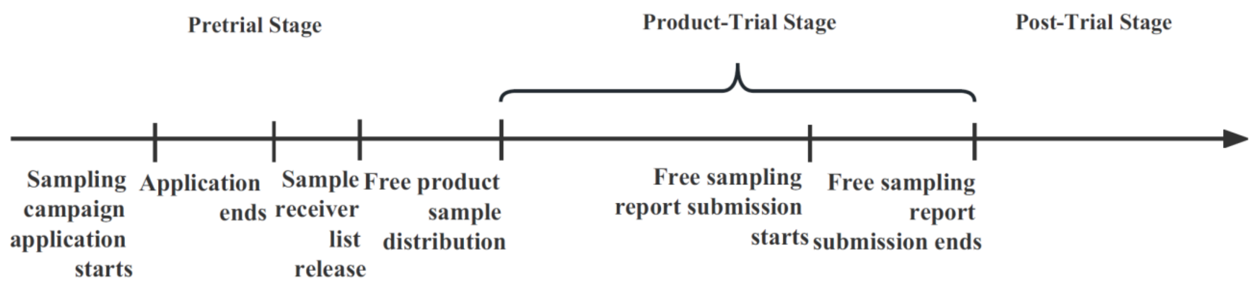

Figure 3: Timeline of a Free Product Sampling Campaign

4.2 Questionnaire Development

The measurements of perceived reciprocity (Pai & Tsai, 2016; Wiertz & de Ruyter, 2007), perceived diagnosticity (Jiang & Benbasat, 2004), product involvement (Laurent & Kapferer, 1985; Zaichkowsky, 1985), advertising information quality (Kim et al., 2009; Zaichkowsky, 1994), and purchase intention (Coyle & Thorson, 2001) were adapted from prior research. All constructs were measured by multiple items on a seven-point Likert scale ranging from 1 = "strongly disagree" to 7 = "strongly agree." Table A.1 in Appendix summarizes the measurement items.

For free sample quantity, free sample diversity, and product rating, we used the objective data collected from the platform by the Python-based data crawler. Free sample quantity is measured as the proportion of the provided sample volume to the original product volume. If the original product has multiple standardized volumes, we choose the minimum product volume. Free sample diversity is measured as the number of different products provided to a focal consumer in a sampling campaign. Product ratings are objective data collected from the platform, as Figure 2 shows. We used the total score as the measurement of product rating. In simultaneous multiple sampling campaigns, more than two products are provided to a consumer at the same time. Campaign participants need to rate all products received separately. We calculated the average score of these products and regarded them as a product package in our data analysis. Control variables included consumer gender, age, income, educational level, skin type, platform tenure, product price, and consumer price perception.

Because we conducted this research in China, we adopted the translation-back-translation method to ensure the accuracy of the Chinese questionnaire and its consistency with the original English measurement instruments. The questionnaire was distributed to two experienced professors, eight Ph.D. students, and 11 consumers as part of a pilot study to preliminarily check for completeness, accuracy, readability, and format of the survey. Based on the feedback, several items were removed, whereas others were corrected or reworded.

4.3 Data Collection

The study was conducted through online questionnaires, which the platform staff distributed to the free sample receivers through WeChat groups. To help consumers better recall their product consumption perceptions and campaign engagement experience, we selected all free product sampling campaigns that had been launched within four months of the questionnaire collection period and that had already sent out their free samples to participants. The questionnaires were sent to all free sample receivers from these campaigns. To attract participants, a small gift (a low-priced beauty and care product) was provided to certain participants. A lucky draw was conducted to select the gift receivers. The questionnaires were distributed to consumers from 31 May 2022 to 5 June 2022. A total of 460 questionnaires were collected. Among these, 118 questionnaires were removed because the respondents had not successfully participated in the free sampling campaigns, had not passed the checking question, or had not submitted the free sampling trial report on the platform. We then conducted survey data screening and detected invalid responses based on the methods proposed in the previous literature (Curran, 2016; Huang et al., 2015). A total of 35 questionnaires failed to pass the detection test. Finally, we had 307 valid responses, a response rate of 66.7%. The average response time was 9.0 minutes.

Table 1 summarizes the demographic profile of the respondents. Among the 307 participants, 279 (90.9%) were female and 28 (9.1%) were male, which was consistent with the main target audience of the platform and the brands on the platform. Females are the primary intended consumers of these beauty and care products. Most respondents were aged between 18 and 25 (63.2%). A total of 87.6% of the participants had a Bachelor's degree or higher, and 80.1% of the participants' monthly income was below 5999 RMB. A total of 78.5% of the participants had more than one year of experience on the platform.

Table 1: Demographics of Respondents

Characteristics	Value	Frequency	Percent
Gender	Male	28	9.1%
	Female	279	90.9%
Age	Below 18	17	5.5%
	18–25	194	63.2%
	26–30	63	20.5%
	31–40	31	10.1%
	Above 40	2	0.7%
Education Level	Junior high school or below	4	1.3%
	High school	34	11.1%
	Bachelor's degree	241	78.5%
	Master's degree or higher	28	9.1%
Monthly Income (RMB)	Below 3000	137	44.6%
	3000–5999	109	35.5%
	6000–9999	40	13.0%
	10,000–19,999	18	5.9%
	Above 20,000	3	1.0%
Platform Tenure	Less than 3 months	4	1.3%
	3 months to 1 year	62	20.2%
	1 year to 3 years	179	58.3%
	More than 3 years	62	20.2%
	Total	307	100%

To further examine the representativeness of our survey sample. We compare the demography of our sample to two populations. The first one is the whole community free sample receivers' population collected from the same platform. We compared the age and occupation distribution of the two populations, and no systematic differences were found. The second one is the China beauty industry consumer demography distribution collected from the industrial research report (iResearch, 2021; LeadLeo, 2020). After comparing the Chinese consumer demography in the beauty and care industry, China's internet users' age composition, and the respondents' demography in this study, the age distribution shows no significant differences. We believe our survey respondents reach a satisfactory level of representativeness of the whole free sample receivers' population.

5. Data Analysis and Results

5.1 Common Method Variance

There is the potential risk of the occurrence of common method variance (CMV) in self-reported data; that is, the variance may be attributable to the measurement method rather than to the constructs the measures represent (Podsakoff et al., 2003). To address this issue, we used several procedural and statistical remedies.

First, the cover letter of our questionnaire assured respondents that their answers would be anonymous and that there were no right or wrong answers to the questions. Further, we paid careful attention to the wording of the items and developed our questionnaire carefully to reduce item ambiguity. These procedures would reduce the respondents' evaluation apprehension and make them less likely to edit their responses to seem more socially desirable, lenient, acquiescent, and consistent with how they thought the investigator wanted them to respond (Podsakoff et al., 2003; Tourangeau et al., 2000).

Second, the independent variable, free sample quantity, and free sampling diversity consisted of objective data collected from the platform. The second dependent variable, product rating, also consisted of objective data. Both subjective and objective data were collected in this study, which helped further reduce the common method bias issue.

Third, we adopted two statistical analytical methods to assess if CMV was problematic to our data. We first conducted Harman's single factor test (Podsakoff et al., 2003). The results showed that the largest extracted factor explained 37.8% of the total variance. This was less than the threshold value of 40%, indicating that CMV was not a major source of the variations in the items (Malhotra et al., 2006). Following the literature, we also used a marker variable to control for common method bias (Lindell & Whitney, 2001). We used the product ID number as the marker variable because it was theoretically unrelated to the other variables (Lindell & Whitney, 2001; Podsakoff et al., 2003). All significant correlations remained significant after the partial correlation adjustment. Although the results of this analysis did not explicitly preclude the possibility of CMV, they did suggest that CMV was not of great concern in this study.

5.2 Assessment of Measurement Model

The measurement model was first examined to ensure that psychological instruments were used appropriately, including reliability and convergent and discriminant validity (Hair et al., 2012). Tables 2 and 3 summarize the results. Cronbach's α was used to assess the reliability of the latent variables. The results exhibited good reliability (i.e., above the threshold value of 0.707) (Nunnally & Bernstein, 1994). Additionally, the composite reliability ranged from 0.902 to 0.975 and was largely higher than the threshold value of 0.7 (Nunnally & Bernstein, 1994), indicating adequate reliability.

Convergent validity was examined by estimating the average variance extracted (AVE) for each latent variable (Table 2) as well as exploring the item loadings and cross-loadings. The AVE scores ranged from 0.697 to 0.909 for each construct, exceeding the benchmark value of 0.5 and indicating that these items explained more variance in the associated construct than measurement error (Fornell & Larcker, 1981). Thus, adequate convergent validity was found.

Discriminant validity was examined by conducting three separate tests. First, we examined item cross-loadings. All items' load was higher on their intended latent construct than its cross-loading on other constructs (Table 2), demonstrating that the items discriminated adequately across constructs (Hair Jr et al., 2017). Second, we conducted the Fornell-Larcker criterion test (Fornell & Larcker, 1981). According to this criterion, the square root of AVE by each latent construct must be higher than its correlation with any other construct (Fornell & Larcker, 1981). The results in Table 3 show that no off-diagonal correlations exceed the square root of the AVE on the diagonal, indicating adequate discriminant validity. Finally, we conducted a Heterotrait-monotrait (HTMT) criterion test (Henseler et al., 2015), which is claimed to be more reliable than the Fornell-Larcker criterion in detecting a lack of discriminant validity (Maier et al., 2021). HTMT values for all constructs were below the conservative benchmark of 0.85 (Henseler et al., 2015) (the highest value is 0.49), providing additional evidence that discriminant validity was not an issue in this study and that the measurement model was valid. Overall, the results demonstrated a satisfactory level of reliability, convergent validity, and discriminant validity.

Table 2: Item Loadings, Cross Loadings, and Reliability

	Item	**1**	**2**	**3**	**4**	**5**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
Purchase Intention (PI)	PI1	**0.936**	0.116	0.047	0.057	0.091	0.966	0.975	0.909
	PI3	**0.932**	0.063	0.102	0.110	0.096			
	PI4	**0.930**	0.110	0.126	0.095	0.078			
	PI2	**0.928**	0.066	0.062	0.128	0.111			
Advertising Information Quality (AIQ)	AIQ2	0.046	**0.869**	0.146	0.210	0.084	0.900	0.930	0.768
	AIQ 3	0.134	**0.865**	0.176	0.204	0.098			
	AIQ4	0.126	**0.809**	0.094	0.145	0.024			
	AIQ 1	0.070	**0.749**	0.184	0.285	0.246			
Perceived Reciprocity (PR)	PR4	0.162	0.154	**0.861**	0.125	0.081	0.880	0.918	0.736
	PR3	0.147	0.116	**0.850**	0.203	0.099			
	PR2	0.120	0.169	**0.668**	0.334	0.372			
	PR1	-0.016	0.252	**0.622**	0.244	0.335			

Consumer Product Involvement (CPI)	CPI3	0.167	0.231	0.144	**0.839**	0.074	0.855	0.902	0.697
	CPI1	0.137	0.292	0.179	**0.755**	0.154			
	CPI4	0.124	0.137	0.286	**0.727**	0.137			
	CPI2	-0.010	0.349	0.239	**0.625**	0.295			
Perceived Diagnosticity (PD)	PD3	0.041	0.001	0.011	-0.006	**0.770**	0.853	0.911	0.774
	PD4	0.194	0.166	0.242	0.220	**0.707**			
	PD2	0.138	0.162	0.398	0.332	**0.644**			
	PD1	0.175	0.241	0.381	0.288	**0.617**			

Table 3: Correlations Between Constructs

	Max	**Min**	**Mean**	**Std**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Quantity	2.00	0.17	1.13	0.36	1							
2. Diversity	4.00	1.00	1.21	0.60	0.485***	1						
3. Consumer Product Involvement	7.00	3.25	6.62	0.61	-0.132*	-0.109	1					
4. Advertising Information Quality	7.00	3.25	6.44	0.73	-0.127*	-0.087	0.569***	1				
5. Reciprocity	7.00	4.00	6.74	0.53	0.024	0.064	0.569***	0.436***	1			
6. Diagnosticity	7.00	4.00	6.53	0.64	0.008	0.017	0.513***	0.375***	0.560***	1		
7. Product Rating	5.00	2.70	4.28	0.49	-0.107	-0.076	0.150**	0.135*	0.221***	0.191**	1	
8. Purchase Intention	7.00	1.00	5.55	1.41	-0.054	-0.110	0.286***	0.243***	0.253***	0.295***	0.443***	1

(Note: *: p < 0.05; **: p < 0.01; ***p < 0.001)

5.3 Assessment of Structural Model

After examining the measurement model, we tested the structural model. We conducted hypotheses testing using SmartPLS 3.0. PLS is highly recommended as a data analytical technique in SEM (Structural Equation Modeling) for studies aiming to predict focal constructs or identify key drivers by extending an existing theory (Hair et al., 2012). The selection of the PLS method resonated with the objectives of this study. Figure 4 displays the data analysis results and Table 4 summarizes the hypothesis testing results.

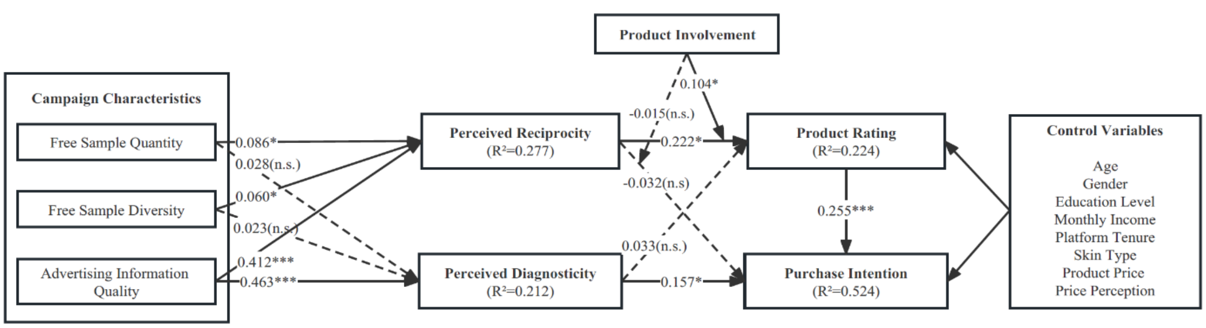

Figure 4: Results of Structural Model

(Note: *: p < 0.05; **: p < 0.01; ***: p < 0.001; n.s.: Correlation is not significant at 0.05)

Overall, empirical evidence supported the majority of the hypotheses proposed. The results revealed that perceived reciprocity had a positive and significant effect on product rating ($\beta = 0.222$, $p = 0.020$), supporting H1. However, the relationship between consumer perceived reciprocity and purchase intention was not significant ($\beta = -0.032$, $p = 0.646$), and H2 was not supported. We then tested the moderating effect of product involvement. Results showed that consumer product involvement had a positive moderating effect on product rating ($\beta = 0.104$, $p = 0.041$), and H3 was supported. The moderating effect on purchase intention was not significant ($\beta = -0.015$, $p = 0.762$); H4 was not supported. These results are interesting. Consumer perceived reciprocity has a positive effect on product rating (attitudinal loyalty) but not on purchase intention (purchase loyalty). There are two possible reasons for this. First, the previous literature has suggested that reciprocity has two predictors, gratitude and obligation (Gouldner, 1960).

Though general sample receivers may feel gratitude toward a platform, their feelings of obligation to repay the favor may vary. Second, the prior literature has posited that there are six types of resources that can be exchanged: love (i.e., an expression of affectionate regard, warmth, and comfort), status, information, money, goods, and services (Foa, 1971). Whether a resource exchange occurs depends on the suitability of the environment and the ability and incentive of the exchangers to give and receive (Foa & Foa, 1974). Product purchases may involve monetary costs, so consumers may not find it necessary to purchase a product to show their gratitude. Consumers with high perceived reciprocity prefer to give a high product rating to show their thankfulness and gratitude instead of spending money to purchase the product, and positive rating effects are stronger when consumers have a higher product involvement.

Interestingly, these results showed an opposite effect on perceived diagnosticity. The relationship between consumer perceived diagnosticity and product rating was not significant ($\beta = 0.033$, $p = 0.704$). H5 was not supported. Meanwhile, the effect of consumer perceived diagnosticity on purchase intention was positive and significant ($\beta = 0.157$, $p = 0.035$), supporting H6. A possible explanation is that perceived diagnosticity helps consumers better understand product quality and increase their product purchase confidence. However, product ratings depend on the actual product quality. Higher perceived diagnosticity does not mean the product will actually be better. Product rating had a positive effect on purchase intention ($\beta = 0.255$, $p < 0.001$), consistent with the findings in the prior literature (Hsu & Lin, 2015). Overall, the variables involved account for 22.4% and 52.4% of the variance explained in product rating and purchase intention, respectively.

As postulated, both free sample quantity ($\beta = 0.086$, $p = 0.042$) and free sample diversity ($\beta = 0.060$, $p = 0.031$) showed a positive and significant effect on consumer perceived reciprocity, thus supporting H7 and H9. However, the effects of free sample quantity ($\beta = 0.028$, $p = 0.642$) and free sample diversity ($\beta = 0.023$, $p = 0.704$) on consumer perceived diagnosticity were insignificant. H8 and H10 were not supported. These results are also explainable. In the product sampling context for beauty and care products, product sample quantity may not help increase consumer perceived diagnosticity because even a small volume of the product may help consumers learn about the product quality. Regarding free sample diversity, the products provided in the sampling campaign usually come from different product categories. Providing products from other categories may not necessarily help consumers better understand the focal product. Consistent with the hypotheses proposed, the results showed positive and significant effects of advertising information quality on perceived reciprocity ($\beta = 0.412$, $p < 0.001$) and perceived diagnosticity ($\beta = 0.463$, $p < 0.001$). Both H11 and H12 were supported. Overall, these factors accounted for 27.7% and 21.2% of the variance in perceived reciprocity and perceived diagnosticity, respectively.

Table 4: Hypotheses Testing Results

Hypotheses	Result
H1: Consumer perceived reciprocity has a positive effect on product rating.	Supported
H2: Consumer perceived reciprocity has a positive effect on product purchase intention.	Not supported
H3: The effect of perceived reciprocity on product rating will be stronger when product involvement is high.	Supported
H4: The effect of perceived reciprocity on purchase intention will be stronger when product involvement is high.	Not supported
H5: Consumer perceived diagnosticity has a positive effect on product rating.	Not supported
H6: Consumer perceived diagnosticity has a positive effect on product purchase intention.	Supported
H7: Free sample quantity has a positive effect on consumer perceived reciprocity.	Supported
H8: Free sample quantity has a positive effect on consumer perceived diagnosticity.	Not supported
H9: Free sample diversity has a positive effect on consumer perceived reciprocity.	Supported
H10: Free sample diversity has a positive effect on consumer perceived diagnosticity.	Not supported
H11: Advertising information quality has a positive effect on consumer perceived reciprocity.	Supported
H12: Advertising information quality has a positive effect on consumer perceived diagnosticity.	Supported

5.4 Mediation Effects Testing

We further conducted mediation effects testing. The prior literature has suggested that three conditions must be fulfilled to establish mediation (Baron & Kenny, 1986). First, the independent variables should significantly affect the dependent variables. Second, the independent variables should significantly affect the mediators. Third, the mediators should significantly affect the dependent variables. The analysis also helped determine whether the influences of the four independent variables on the dependent variables were significantly reduced (partial mediation) or completely eliminated (full mediation) when perceived reciprocity and perceived diagnosticity were included simultaneously with the four independent variables.

Bootstrapping procedures (bootstrap sample size = 5000) were adopted to test the mediating effects as the prior literature recommended (Preacher & Hayes, 2004). Compared to the conventional Baron and Kenny (Baron & Kenny, 1986) and Sobel (Sobel, 1982) methods, the bootstrapping method has several advantages, including larger statistical power, lack of assumption of a normal distribution, and allowance for direct measurement of mediating effects. Asymmetric confidence intervals (CIs) were calculated to estimate the mediating effect of the indirect relationship. If zero was not included in the 95% CIs, the mediating effect was significant (Preacher & Hayes, 2004). Table 5 summarizes the test results. The results indicated that perceived reciprocity mediated the relationship among free sample quantity, free sample diversity, advertising information quality and product rating. Perceived diagnosticity mediates the relationship between advertising information quality and purchase intention. The bootstrapping results showed that perceived reciprocity mediated the effect of free product quantity (95% CI [0.0417, 0.0617]), free product diversity (95% CI [0.0670, 0.0871]), and advertising information quality (95% CI [0.0070, 0.0689]) on product rating. Perceived diagnosticity mediates the effect of advertising information quality (95% CI [0.0014, 0.1539]) on purchase intention.

Table 5: Mediation Effect Test Results

	Purchase Intention	Product Rating	Perceived Reciprocity	Perceived Diagnosticity	Purchase Intention	Product Rating
Free Sample Quantity	-0.089*	0.063*	0.086*	0.029	-0.058	-0.042
Free Sample Diversity	0.189*	-0.284**	0.072**	0.023	0.010	-0.224
Advertising Information Quality	0.012**	0.053**	0.165***	0.180***	0.012	0.032
Perceived Reciprocity					-0.046	0.247**
Perceived Diagnosticity					0.078*	0.029
Adjusted R^2	0.481	0.110	0.436	0.385	0.480	0.131
F	19.343	3.635	14.896	11.581	17.098	3.490

(Note: *: p < 0.05; **: p < 0.01; ***p < 0.001)

6. Conclusions

We examined the different impacts of consumer perceived reciprocity and perceived diagnosticity on customer loyalty. Specifically, consumer perceived reciprocity was found to positively affect attitudinal loyalty (product ratings) but not purchase loyalty (purchase intention). Consumer product involvement positively moderates the relationship between perceived reciprocity and product rating. Meanwhile, consumer perceived diagnosticity positively influences purchase loyalty (purchase intention). Its effect on attitudinal loyalty (product ratings) is not significant. We further investigated how sampling campaign characteristics affect consumer perceived reciprocity and perceived diagnosticity. The results showed that free sample quantity and free sample diversity have positive effects on perceived reciprocity. Their effects on perceived diagnosticity are not significant. Advertising information quality positively affects both perceived reciprocity and perceived diagnosticity. This research was the first to investigate the impacts of free product sampling campaign characteristics (free sample quantity, free sample diversity, and advertising information quality) on consumer perceptions, product rating, and purchase intention, enriching and extending the product sampling and customer loyalty-related literature. The research findings contribute to both academics and practitioners.

6.1 Theoretical Contributions

This study offers three theoretical contributions. First, this study provided empirical evidence of reciprocity and diagnosticity effects in the free product sampling context and examined their different roles on consumer attitudinal loyalty (product ratings) and purchase loyalty (purchase intention). Previous literature mainly concentrates on the single reciprocity effect (Bawa & Shoemaker, 2004). This study takes both the reciprocity effect and diagnosticity effect into consideration and empirically examines their different roles in two types of customer loyalty. Though reciprocity perception was found to be an important construct in the product sampling context (Lin et al., 2019; Pu et al., 2021), this study found that it does not necessarily increase consumer product purchase intention (purchase loyalty). Existing literature has posited that there are different types of resources that can be used for exchange in reciprocity (Foa, 1971). This study found that free sample receivers are more likely to give a higher rating to show their thankfulness and gratitude instead of paying the monetary cost to purchase the product. We further found that diagnosticity perception is a more important determinant that affects consumer purchase intention in the free product sampling context.

Second, this study enriches and extends the product sampling literature by taking different product sampling characteristics into consideration. This study was the first to investigate the impacts of different product sampling strategies (free sample quantity, free sample diversity, and advertising information quality). Our study went beyond well-investigated monadic product sampling strategies and took simultaneous multiple product sampling strategies into consideration. Simultaneous multiple product sampling strategies could generate higher consumer reciprocity perception. We also highlighted the important role of campaign advertising information quality on perceived reciprocity and perceived diagnosticity.

Third, this study was among the first to empirically investigate free sample receivers' product and campaign reactions. The existing literature has mainly focused on estimating and quantifying the impacts of free product sampling engagement at a product level. Sample receivers' perceptions toward the product sample and sampling campaign have been largely overlooked. This study collected multi-source data, including subjective survey data from real free sample receivers and objective data from the campaign platform, to help reveal sample receivers' cognitive (perceived diagnosticity) and affective reactions (perceived reciprocity) in free product sampling campaigns.

6.2 Practical Implications

For practitioners, product sampling comes at a price. It is important for brands and platforms to choose appropriate sampling strategies and wisely manage their product sampling campaigns. This study provides practical implications for choosing appropriate product sampling strategies for various products. Its results suggested that increasing sample quantity and sample diversity would be a good way to increase consumer perceived reciprocity. Additionally, increasing advertising information quality is critical for building perceived reciprocity and perceived diagnosticity. Brands and platforms should try to increase the quality and attractiveness of sampling campaign advertisements. Finally, the results showed that perceived reciprocity helps increase product ratings but not purchase intention. If brands aim to increase product sales through product sampling, increasing consumer perceived diagnosticity would be an appropriate choice.

6.3 Limitations and Future Research

Despite the contributions of this study, it has several limitations and provides research directions for future studies. First, this study collected cross-sectional survey data to test the research model. Future studies can collect actual sales data to further explore the impacts of different free product sampling characteristics on sample receivers' actual purchase behaviors. Second, this study only focused on three sampling campaign characteristics: free sample quantity, free sample diversity, and advertising information quality. Future studies can explore more interesting sampling campaign characteristics according to their specific research contexts. Third, the main respondents and consumers in this context were females. The research findings may not be appropriately applied to male consumers. Future studies can explore whether there are any gender differences in free sample consumption experiences and consequences.

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Appendix. Measurement Items

Table A.1: Survey Measurement Items

Construct	Survey items	Reference
Perceived Reciprocity (PR)	PR1. I appreciate receiving this free trial product. PR2. I feel an obligation to help the platform achieve its goals. PR3. When I received the free product samples from this platform, I felt it was right to give back and help it. PR4. When I received the free product samples from this platform, I felt obligated to help the community/brander if it needed my help.	(Pai & Tsai, 2016; Wiertz & de Ruyter, 2007)
Perceived Diagnosticity (PD)	PD1. Overall, this free product trial experience helps me to judge the quality and performance of the product. PD2. Overall, this free product trial experience helps familiarize me with this product. PD3. Overall, this free product trial experience could influence my overall evaluation of this product. PD4. Overall, this free product trial experience enabled me to accurately evaluate the product presented.	(Jiang & Benbasat, 2004)
Consumer Product Involvement (CPI)	CPI1. When I buy a similar product, product information is very important to me. CPI2. I will carefully compare whether different product quality is good or bad before purchasing similar products. CPI3. I have always wanted to learn more about similar products and enjoy it when people teach me about them. CPI4. Beauty and care products interest me and are an important hobby to me.	(Laurent & Kapferer, 1985; Zaichkowsky, 1985)
Advertising Information Quality (AIQ)	AIQ1. The product advertising information provided by the platform is important to me. AIQ2. The product advertising information provided by the platform is appealing to me. AIQ3. The product advertising information provided by the platform is valuable to me. AIQ4. The product advertising information provided by the platform is exciting.	(Kim et al., 2009; Zaichkowsky, 1994)
Purchase Intention (PI)	PI1. It is likely that I will buy this product. PI2. I will purchase this product the next time I need a product. PI3. If a friend called me to get my advice about which product to buy, I would advise them to buy this product. PI4. Overall speaking, I would buy it if I had a budget.	(Coyle & Thorson, 2001)
Price Perception (PP)	PP1. The price of this product suits my buying power. PP2. The price of this product is more efficient than other similar products. PP3. The price of this product meets the product’s quality. PP4. The price of this product is affordable.	(Widyastuti & Said, 2017)