Journal of Retailing and Consumer Services 89 (2026) 104596

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

Introducing the adaptive "Dual Response" Kano method – conceptualization and empirical application

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ARTICLE INFO

Keywords:
Kano
Dual Response Kano
Retailing
Concept stores
Omni-channel
Digitalization

ABSTRACT

While the theory of attractive quality and the related Kano method received popularity in the past, recent research increasingly criticizes its shortcomings. Two unresolved shortcomings are (i) what to do with the (many) attributes classified as "indifferent" and (ii) controlling for the link between (high levels of) satisfaction and behavior. To overcome these problems, the adaptive "Dual Response" Kano method is proposed, which allows to clarify implications for "indifferent" attributes and scrutinizes respondents' behavioral intentions for high satisfaction levels. Additionally, it enables prioritizing which (attractive) attributes should be realized first (prioritization) to achieve a certain behavior. The Dual Response Kano method is illustrated in the context of revisiting concept stores after the pandemic with a representative sample of $n = 607$ German consumers. The results emphasize the necessity of controlling for behavioral intentions even for attractive attributes. Moreover, some attributes hitherto classified as "indifferent" could actually increase visiting behavior ("latent potentials").

1. Introduction

The Kano model was introduced in 1984 by Professor Noriaki Kano and colleagues, and received notable popularity for examining consumers' satisfaction with a product/service in the past (Löfgren and Witell, 2008). However, in recent years, an increasing number of articles have criticized the Kano model (Zhang et al., 2023). For instance, Shahin et al. (2013, 2017) and Yang (2005) noticed problems with too many attributes being categorized as "indifferent". It is not clear what to do with such attributes in regular Kano investigations. Recent Kano investigations prove that many attributes will be classified as indifferent (e.g., Rese et al. (2019): 40 %; Stöcker et al. (2021): 90 %; 36 %; 22 %; Baier and Rese (2020): 68 %). The problem may, in part, be caused by the Kano classification table (see, e.g., Löfgren and Witell, 2008), which assigns the attributes analyzed into the "indifferent" classification in 36 % of all possible categorizations (see Fig. 1). In response, some researchers have started to suggest alternative evaluation tables that classify seven indifferent categories into four sub-groups (Shahin et al., 2013, 2017) or differentiation based on additional importance measures (Yang, 2005). Yet, researchers/practitioners are still left with no clear implication of what (not) to do with these "indifferent" attributes.

Another criticism focuses on satisfaction as the dependent variable (instead of, e.g., (purchase) behavior). Plenty of research indicates a strong link between consumer satisfaction and actual consumer behavior, such as sales performance (Gómez et al., 2004). However, the vast majority of studies using the Kano method do not measure subsequent behavior but only satisfaction. As a result, recent studies employing the Kano method call for the assessment of actual performance metrics (e.g., purchase intention) along with the consumer satisfaction questions (Baier and Rese, 2020). If investigations applying the Kano method fall short of asking relevant, additional features, the estimation of the parameters used can be biased (Finn, 2011). Similarly, the satisfaction assessment depends on (cognitive) reference points (Szymanski and Henard, 2001). Imagine, for example, a study evinces smart mirrors to be the best rated attribute to increase satisfaction (i.e., "attractive") for retail stores, but the list of attributes is incomplete (e.g., not covering an option "parking spaces"). Then, consumers might actually evaluate sufficient parking spaces as much more important and thus, not visit a store even if smart mirrors are installed, because the parking situation is unsatisfactory. Since the relationship between attribute performance and consumer satisfaction does not necessarily need to be symmetric, this constitutes a substantial shortcoming in the literature (Arbore and Busacca, 2009).

Several of these proposed optimizations of the Kano model and the

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https://doi.org/10.1016/j.jretconser.2025.104596
Received 24 April 2025; Received in revised form 3 October 2025; Accepted 23 October 2025
Available online 10 November 2025

way it is being analyzed may improve the measurement precision and thus, increase the validity of the findings. Nevertheless, no article has examined (i) how to deal with attributes classified as "indifferent" and (ii) to what extent satisfaction will result in actual behavior. To address these two literature gaps, we aim to provide three methodological contributions by introducing an extension to the Kano method (i.e., the "Dual Response Kano method"). First, this Dual Response Kano method includes an adaptive feature, which sheds light on what to do with an attribute – in case respondents selected answers leading to its classification as "indifferent". More precisely, it asks respondents if a feature is "wanted" or not. Second, having multiple features that were presumed to be "indifferent" but are actually wanted would result in the initial ambiguity without clear implications of what to do. Therefore, an additional adaptive question at the end of the Kano survey asks respondents which of the wanted attributes is most wanted and most likely to result in a certain behavior (e.g., visiting a store more often). This feature not only examines the link between satisfaction and behavior, but also allows us to derive (practical) implications on an individual level. Hence, the Dual Response Kano method enables researchers to analyze for which consumer (segments) the related indifferent attribute may still be worth reconsidering – especially, in case where there are plenty of indifferent attributes and no attractive ones. This approach is in line with previous research that added sub-classifications for one-dimensional attributes and found that additional differentiation can counteract weaknesses of the Kano method (Vaez-Shahrestani et al., 2020). Third, it empirically tests the link between an attribute's performance on behavior on an individual basis.

Apart from these methodological insights, the adaptive Dual Response Kano method will be illustrated with an example of how to bring customers back to brick-and-mortar stores after the pandemic using a representative sample of $n = 607$ German consumers. Various smaller retailers face difficulties in returning to the number of customer visits and sales of pre-pandemic times (Alvarez and Marsal Holdings, 2021), and omni-channel solutions may help solve this problem (Sheth, 2021). However, digital transformations are more difficult for small retailers with fewer financial resources. This might be particularly the case for concept stores, whose main aim is to create new, additional touchpoints, offer a source of inspiration, and attract new (former latent) customers with a broad range of different needs (Egan-Wyer et al., 2021). Concept stores, a rather nascent phenomenon that has not yet been sufficiently researched, offer such an optimized customer journey with high convenience and accessibility more than other store formats (Egan-Wyer et al., 2021). To implement digital solutions in concept stores that enhance the interface between offline and online customer experiences (Rese et al., 2019), it is crucial to know which digital solutions are worth investing in (Baier and Rese, 2020). Research exists on consumers' perception of new technologies in retail in general. However, "[a] critical area of inquiry pertains to ensuring an effective understanding of how consumers respond to new technologies" (Plangger et al., 2022, p. 1125), especially for innovative formats like concept stores.

Hence, this paper's contributions are two-fold. First, the methodological extension ("Dual Response" Kano) (i) helps researchers and practitioners alike to identify the measures needed when there appears to be no clear implications. Additionally, it (ii) empirically challenges the previously established assumption of the Kano method that high consumer satisfaction (automatically) translates into actual, desirable consumer behavior (such as more purchases or store visits; Finn, 2011). As a result of the methodological extension, using this newly introduced approach underlines the need to add (control) questions about actual behavior and entails more granular insights with distinct implications for researchers and practitioners. Additionally, it emphasizes the need to separately control for customers' behavior (instead of the upstream proxy "satisfaction"). Second, we enrich the scarce literature on concept stores by analyzing which digital solution can increase customer satisfaction. Similarly, we shed light on which digital solutions can motivate consumers to revisit concept stores. These findings can help retailers offer the solutions needed to increase the number of shop visitors (after the pandemic) and, ultimately, increase sales. Furthermore, this study contributes to the literature by providing a state-of-the-art overview of consumers' satisfaction with varying digital solutions in concept stores. According to the theory of attractive quality, the evaluation of such technologies changes over time (Nilsson-Witell and Fundin, 2005), emphasizing the importance of keeping insights on these solutions up to date.

2. Literature review of methodological development of the Kano method

In 1984, Kano and colleagues introduced the Kano model and the related Kano method to the context of quality management (Kano et al., 1984). They transferred Frederick Herzberg's two-factor theory - also known as Herzberg's Motivator-Hygiene theory - to a model that identifies and classifies quality attributes based on their influence on customer satisfaction. Herzberg and colleagues (1959) found that job satisfaction and dissatisfaction are not a continuum, but two distinct concepts. While hygiene factors are the primary reason for job dissatisfaction, motivator factors are the primary reason for job satisfaction. Correspondingly, the two concepts have their own set of influencing factors (Berger et al., 1993; Herzberg et al., 1959). Kano et al. (1984) suggested linear and non-linear relationships between customer performance and quality attributes. The differences manifest themselves in five distinct attribute categories each with a different relationship to satisfaction: must-be (M), attractive (A), one-dimensional (O), reverse (R), and indifferent (I). A sixth category includes illogical answers (questionable (Q)), for instance, when both the functional and dysfunctional question are liked or disliked. From a methodological perspective, the Kano model provides several approaches and graphical representations for sorting attributes into categories. Berger and others (1993) introduced various features of the Kano method that are currently established: the Kano model questionnaire with a functional and a dysfunctional question, the related response options, the Kano diagram displaying the relationship between feature fulfillment (dysfunctional - functional) and customer satisfaction of the different classifications, the Kano model evaluation table, the Kano model results table, and the two-dimensional grid based on customer satisfaction and dissatisfaction coefficients with four quadrants (Berger et al., 1993). Additionally, Berger et al. (1993) introduced the prioritizing rule "$M > O > A > I$". Later on, Lee and Newcomb (1997) developed the measures of category strength ($\geq$6 % difference between two categories) for categorizing attributes and total strength (sum of %-values of A, O, and M; see also section 5).

In the 1990s, the first applications were published in the US (Lee and Newcomb, 1997) and Europe, with the Kano method also being combined with the Quality Function Deployment (Matzler and Hinterhuber, 1998). In 2005, Yang conceptually proposed a differentiation within "indifferent" attributes (i.e., potential quality and care-free attributes). Firms should pay attention to "potential quality" attributes, as they help attract new customers. In contrast, firms need not necessarily implement care-free quality attributes. However, a prioritization or selection rule for presumed "indifferent" attributes is missing. In addition, using the approach by Yang (2005), the survey needs to be extended for each and every Kano item by an additional measure of importance and satisfaction on 5-point Likert scales. By now, the Kano model has been used in numerous studies across different industries, with several literature reviews record its prevalence in research (e.g., Löfgren and Witell, 2008; Slevitch, 2024). For our overview of the development and adjustments of the Kano model, we used phases presented by Witell et al. (2013): Emergence (1984–1999) and Exploration (2000–2011), with the latter extended until 2022. We renamed the last phase Refinement instead of Explosion (see Appendix A), since the related research focuses on adjustments of the method (while a large number using the Kano method were published in this period). The Exploration phase includes modifications of the wording of Kano questions or connecting the Kano model with other qualitative and quantitative approaches for attribute classification (for an overview see, e.g., Slevitch, 2024). Furthermore, the additional sub-categories for the Kano classification scheme that rely on additional importance measures (Yang, 2005) together with improvements to the evaluation table fall within this phase. In the Refinement phase, new approaches are related to supplementing or replacing the Kano questionnaire (e.g., Shahin et al., 2017; Song, 2018). Here, particularly machine learning approaches are on the rise, which use online reviews to identify attributes for the Kano survey (Bi et al., 2019; Kim et al., 2025; Xiao et al., 2016; Zhang et al., 2023). Recent research shows that approaches relying on transformative functions for the conversion of utility values into satisfaction scores yield fewer numbers of indifferent attributes (Zhao et al., 2024). In addition, research has made attempts to deal with the problem of too many indifferent attributes by adding sub-classifications (e.g., Shahin et al., 2017). Similar to the work by Yang (2005), no prioritization or a selection rules were proposed (Shahin et al., 2017).

The proposed "Dual Response" Kano method moves beyond these previous milestones, offering a mechanism to identify and prioritize actually wanted, but yet presumed "indifferent" attributes depending on consumers' response patterns. Additionally, respondents' behavioral intentions for high satisfaction levels are revealed and a prioritization of which wanted attributes should be implemented (first) is provided.

3. Theoretical background for Dual Response Kano method

Regardless of these optimizations and refinements, two problems of the Kano method remain unsolved: (i) what to do with attributes categorized as indifferent and (ii) the link between (high levels of) satisfaction and behavior, e.g., do high levels of satisfaction automatically translate into corresponding behavior?

3.1. *Clarifying implications for indifferent attributes*

Out of all potential classifications, 36 % of the answer combinations from the dysfunctional and functional question will result in the attribute being classified as "indifferent" (see Fig. 1). While the likelihood of each classification is not equally distributed, previous studies show that many investigated attributes will ultimately be classified as indifferent (e.g., Baier and Rese, 2020; Stöcker et al., 2021). As a result, researchers and practitioners alike are left with no clear indication of what to do with these attributes. Especially, when the selection of attributes leads to all/most attributes being classified as indifferent, researchers/practitioners will end up with no insights/benefits at all (after investing time and money to create such examination). To counteract such unfortunate issues and allow researchers to (still) gain insights, we introduce the Dual Response Kano method.

Some researchers have started to propose alternative evaluation tables with sub-classifications for attributes trending towards another classification (Shahin et al., 2017) or differentiation based on additional importance measures (Yang, 2005). However, they are still left with no clear indication of whether these "indifferent" attributes should be added to a product/service. More precisely, Yang (2005) suggested distinguishing the indifferent attributes with "care-free quality" and "potential quality" attributes. The latter clearly indicates that some attributes classified as indifferent may actually turn out to be important to (specific segments of) customers. These potential quality indifferent attributes are further defined as "These attributes will gradually becoming the attractive attributes. Firms can consider providing these as strategic weapons to attract customers in the future" (Yang, 2005, p. 1131).

Another differentiation between indifferent attributes was made by Shahin et al. (2017). Accordingly, based on the Kano model with its two axes (functionality and satisfaction), some indifferent attributes appear to have a tendency toward reverse attributes, whereas other indifferent attributes are somewhat closer to must-be, attractive, one-dimensional attributes, or represent pure indifference. Additionally, they proposed differentiating between three different types of those indifference attributes with a tendency to reverse ones (i.e., indifference towards reverse attributes toward attractive, toward one-dimensional, toward must-be). In total, they suggested seven different types of indifferent attributes, whereas only one presents a purely indifferent attribute. This research clearly emphasizes the need to differentiate between different categorizations of indifferent attributes. Moreover, it indicates that some attributes classified as "indifferent" may actually be noteworthy, due to their tendency to, for instance, must-be or attractive attributes.

In the Dual Response Kano method, this issue is resolved by adaptively clarifying whether or not potentially "indifferent" attributes are truly indifferent to respondents on an individual level. Since "indifference" as a pathological phenomenon depends on (i) the angle/perspective from which it is viewed and (ii) the approach used to assess indifference, its definition may vary accordingly (Shahin et al., 2017). Accordingly, the Dual Response Kano method dissolves this vagueness by specifically asking each individual respondent an additional question

		Dysfunctional Question				
		I like it that way	I expect it that way	I am neutral	I can accept it to be that waty	I dislike it that way
Functional Question	I like it that way	Q	A	A	A	O
	I expect it that way	R	I	I	I	M
	I am neutral	R	I	I	I	M
	I can accept it to be that way	R	I	I	I	M
	I dislike it that way	R	R	R	R	Q

Fig. 1. Classification of attributes dependent on responses (based on Kano et al., 1984; Matzler and Hinterhuber, 1998). Note: A = attractive, M = must-be, O = one-dimensional, I = indifferent, Q = questionable, R = reverse attributes.

in case the answers selected would result in a classification as indifferent. More precisely, a display logic (similar to skip logics, but instead of skipping questions, questions will be displayed when certain conditions are met) is used. In case the combinations of the answers for the functional and dysfunctional question for an attribute would result in a classification as "indifferent" based on the evaluation table (see Fig. 1), an additional question will instantly appear on the same page. This adaptive question clarifies if the attribute, which would otherwise be classified as indifferent, is rather wanted or not (see Fig. 2).

Based on this adaptive approach and the arguments raised by previous literature (Shahin et al., 2017; Yang, 2005), the following assumption (A1) emerges:

A1: Multiple attributes classified as "indifferent" are actually wanted by the majority (>50 %) of respondents.

Since having multiple "rather wanted" attributes over the course of the questionnaire would result in having the same indistinctness/problem as the conventional Kano method, there is one additional question at the end of the Kano questions. If there are at least two rather wanted attributes, this question displays all those attributes marked as "rather wanted" and asks for the one attribute that is the most wanted attribute (see Fig. 2) to result in a certain behavior (e.g., visiting concept stores more often). Hence, this approach also allows (i) prioritization of all wanted "indifferent" attributes, as well as (ii) determining which one is most likely to cause actual behavior.

This adaptive approach is inspired by the dual response choice design suggested for receiving additional information in conjoint investigations (Brazell et al., 2006). Accordingly, when respondents choose the "no choice" option in a choice experiment, researchers/practitioners are left with no information about the relative attractiveness of the other choices shown. Therefore, Brazell et al. (2006) suggested having a dual response approach, where respondents are asked to select their preferred choice between different options first, before subsequently asking about these options and an additional no choice option. While these adaptive dual response approaches to gain additional in-depth insights are receiving increasing popularity for conjoint designs (Kopplin, 2021; Schlereth and Skiera, 2017), there is no such approach for the Kano model yet.

3.2. Challenging the link between satisfaction and behavior

The second issue solved by the Dual Response Kano method focuses on the only dependent variable (i.e., customer satisfaction) collected and the underlying assumption that high satisfaction levels will (automatically) translate into related behavior. Based on the service-profit chain (e.g., Heskett et al., 1994; Hogreve et al., 2021), high levels of customer satisfaction will lead to high levels of customer loyalty, which, in turn, results in revenue growth and profitability (see Fig. 3). However, the assumed direct link between customer satisfaction and corresponding behavior (e.g., purchases, store visits) that leads to revenue growth is not being examined in the conventional Kano method. Therefore, the Dual Response Kano method uses an adaptive design to control for customers' behavioral intention (instead of using satisfaction as an indirect proxy for behavior). However, we must acknowledge that behavioral intention is still a proxy for actual behavior. Behavior-intention discrepancies might occur, for example, due to different beliefs in hypothetical and real contexts (Brand, 2025).

More specifically, the Dual Response Kano method asks respondents at the end of the Kano survey whether those attributes classified as "attractive" will result in a certain behavior or not. Again, a display logic serves as technical vehicle and asks if the corresponding attribute(s) (i) will result in a certain behavior, (ii) will not result in a certain behavior, or (iii) neither. However, these response options may be adjusted with more/fewer options to yield more/less granular insights about customers' behavior (e.g., likelihood of behaving in a certain way). For example, if the attribute 'smart mirrors' is classified as attractive (satisfaction), the final page of the Kano survey will then ask whether smart mirrors lead to increased store visits (behavior).

Customer satisfaction (usually) leads to customer loyalty, which in turn, results in profitability and/or revenue growth (Hogreve et al., 2021). However, we challenge the implied assumption that increased customer satisfaction (based on "attractive" attributes) will automatically translate into the desired behavior (e.g., more store visits). This assumption also evolves from literature, which argues that the estimation of parameters will be biased, if the Kano method does not include relevant, additional features (Finn, 2011). Additionally, assessing an attribute depends on cognitive reference points (Szymanski and Henard, 2001). Thus, even attractive attributes may not result in a desired outcome when other, more important reference points are omitted from the Kano survey. Therefore, we assume:

A2: Multiple attributes classified as "attractive" will actually not result in the desired behavior.

This approach is very important to check whether satisfaction actually translates into behavior, since (purchase) behavior may depend on other crucial attributes not included among the Kano attributes (Baier and Rese, 2020). For instance, a smart mirror (queried) may increase customer satisfaction in general, but customers will not attend a store

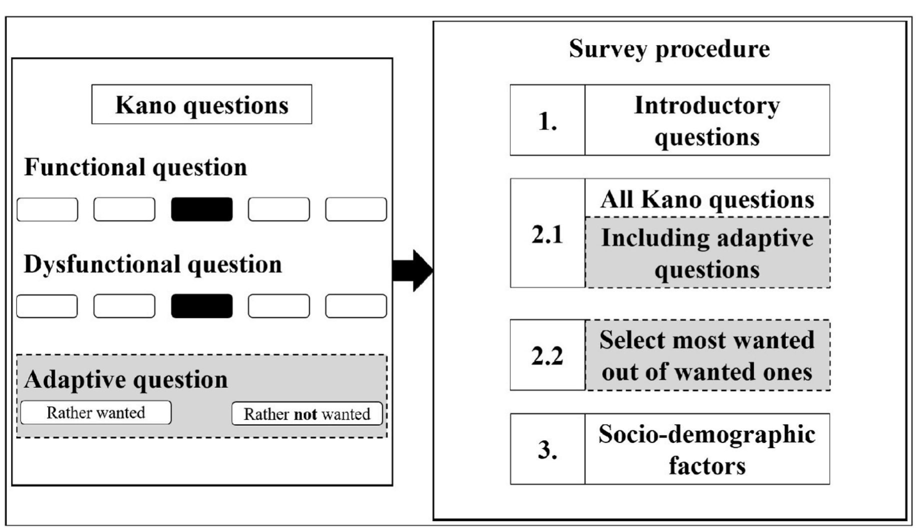

Fig. 2. Classification of attributes dependent on responses (own illustration) *Note: Questions that may or may not appear depending on answers provided are highlighted in grey.*

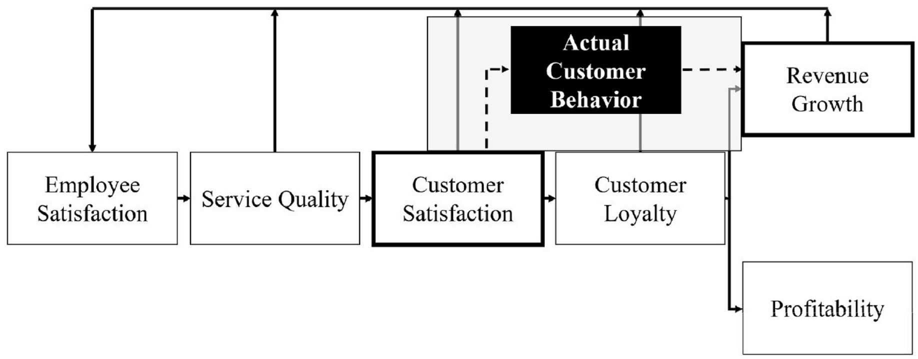

Fig. 3. Service-profit chain extended by controlling for behavior (based on Hogreve et al., 2021).

when parking lots (not queried) are missing. In this case, even high satisfaction for an attribute will not result in the (implicitly assumed) behavior.

Additionally, this adaptive feature of the Dual Response Kano method allows prioritizing which attribute is most likely to result in a certain behavior. While the conventional Kano method uncovers all attributes classified as "attractive", the adaptive feature allows ranking the attribute features that are most frequently indicated for resulting in a behavior.

4. Method

The Dual Response Kano method will be illustrated in the context of how to bring customers back into brick-and-mortar stores (using digital technologies) after the pandemic. Previous research has shown that digital technologies can foster consumers' intention to visit brick-and-mortar stores (Breugelmans et al., 2023; Chang and Chen, 2021). However, not all retailers can afford to invest in such digital technologies. This may be particularly true for concept stores, whose main idea is to create new, additional touchpoints, serve as a source of inspiration, and attract new customers with a variety of different needs (Egan-Wyer et al., 2021). This type of retail store is particularly needs solutions to entice customers to visit brick-and-mortar stores (again). Concept stores are a relatively nascent phenomenon (yet underresearched), offering an optimized customer journey with higher convenience and accessibility than previous store formats (Egan-Wyer et al., 2021). Only some specific digital solutions for retail stores increase customer satisfaction, while others do not (Baier and Rese, 2020). Therefore, it becomes crucial to know which digital solutions can increase customers' satisfaction in concept stores.

Based on $n = 2$ expert interviews with owners of concept stores and complemented by a literature review, nine promising digital technologies were identified for the Dual Response Kano method. For the complementary literature research, we compared ten papers about digital technologies in brick-and-mortar stores. The nine most frequently discussed digital technologies were included in the survey: smart mirrors (mirrors that use Augmented Reality to display products next/on the customer), scatter walls (digital wallboards that display product-related social media posts), additional tablets in stores (for searching for product-related information, using the related online shop, etc.), QR codes on products (to receive additional information), free customer WiFi, an Easy Consulting Button (placed at different points in the store for receiving help from the staff), e-wallet/mobile payment solutions (enabling payment via smartwatch/smartphone), self-service checkouts (customers scan and pay for products themselves), and an app-based bonus program (collecting bonus points for purchases that enable receiving benefits).

The survey itself started with a brief explanation of what concept stores are (including an exemplary illustration). Subsequently, respondents were asked about the frequency of visiting concept stores before the pandemic and their attitude towards these stores. Before the Kano questions, respondents were asked to imagine the scenario of visiting a concept store. For each of the nine digital technologies, a brief description of the technology (including exemplary pictures) was followed by the functional and dysfunctional question, as well as the adaptive Dual Response question depending on the answers provided (i.e., rather wanted or not for "indifferent" attributes). The Kano part of the survey concluded with the adaptive questions concerning the most wanted digital technology of the indifferent wanted ones (Fig. 2), as well as the behavioral control question for technologies classified as "attractive" (depending on respondents' answers). Accordingly, if at least one digital technology was classified as "attractive" based on the answers provided, the survey listed these digital technologies along with the options "Leads to more frequent visits of concept stores", "nor/neither", and "Does not lead to more frequent visits of concept stores".

For sampling, we used an established panel provider (i.e., Kantar) to acquire German consumers of Generation Y. We selected this generation since they are one of the most important consumer segments for shopping (Robichaud et al., 2024) and extremely tech-savvy (Brand and Baier, 2022; Rese et al., 2019). Generation Y is known not only for its substantial purchasing power and advanced technological skills, but also for covering segments with the highest amount of money typically spent in online but not yet in offline shopping (Brand and Baier, 2022). The sample acquired is representative with regard to gender within this age group. The focus on this generational cohort (age) and a representative gender split within this group were the only selection criteria employed. However, the final sample shows a balanced distribution across different sizes of places of residence (see Appendix B). Accordingly, potential biases concerning the adoption of retail innovations between rural and urban areas can be assumed to be absent. The recruitment started with a soft launch of 10 % of the intended sample size (i.e., $n = 62$) in 2021. Since the soft launch did not reveal any errors, the remaining responses were collected. After acquiring a total of $n = 682$ data points, $n = 6$ respondents were younger and $n = 10$ older than the formulated target group communicated to the panel provider. Besides, $n = 41$ did not complete the survey, which leaves $n = 625$ completes. Subsequently, we eliminated speeders resulting in a sample of $n = 607$ respondents. The sample consists of 51.6 % women, and is 32 years old ($SD = 5.47$) on average (for more socio-demographic information see Appendix B). Since all questions were set to "force respondents", there are no missing data fields.

5. Results

While almost half of the respondents had not visited a concept store before the pandemic (47 %), most respondents indicated a neutral (42 %) or rather positive attitude (41 %) towards concept stores. The main Kano results (see Table 1) reflect the tendency noted in previous literature that many attributes are classified as "indifferent". More precisely, each of the nine attributes is classified as indifferent (only the free WiFi

Table 1
Main Kano results.

Digital technologies	M	O	A	I	R	Q	Category	Category Strength	Total Strength	Fong test	*CS-*	*CS+*
App-based bonus program	13	56	216	275	23	24	I	10%	47%	Sign.	-0.123	0.486
Smart mirror	5	42	229	276	33	22	I	8%	45%	Sign.	-0.085	0.491
Self-service checkouts	15	34	182	307	45	24	I	21%	38%	Sign.	-0.091	0.401
Easy Consulting Button	4	24	198	327	38	16	I	21%	37%	Sign.	-0.051	0.401
QR code at products	9	31	176	332	36	23	I	26%	36%	Sign.	-0.073	0.378
e-Wallet payments	52	52	118	335	35	15	I	36%	37%	Sign.	-0.187	0.305
In-store tablets	8	18	179	360	24	18	I	30%	34%	Sign.	-0.046	0.349
Scatter walls	7	14	95	395	78	18	I	49%	19%	Sign.	-0.041	0.213
Free in-store WiFi	46	71	187	258	19	26	I → A*	12%	50%	Sign.	-0.208	0.459

*Note: classification most frequently mentioned highlighted in grey; *based on the "(O+A+M) > (I+R+Q) → (O,A,M)" rule, free in-store WiFi becomes classified as "attractive"*

becomes "attractive" after using the "(O + A + M) > (I + R + Q)" rule (Berger et al., 1993)). This finding might be even more crucial given that previous Kano studies about digital technologies for brick-and-mortar stores oftentimes used convenience samples (e.g., Baier et al., 2020; Finn, 2011) or lower sample sizes (e.g., Chang and Chen, 2014 with $n = 20$; Yang, 2005 with $n = 150$; Gruber et al., 2011 with $n = 272$). Since this study is more reliable being based on a representative sample of $n = 607$ respondents, the issue of facing many attributes classified as "indifferent" seems to be more prevalent than expected.

In addition to the common analysis with categorizing the attributes depending on their frequency, the Category and Total Strength (Lee and Newcomb, 1997), as well as the Customer Satisfaction coefficients (*CS+; CS-*) and the Fong test (Fong, 1996) were examined. Accordingly, the Category Strength can be calculated by subtracting the percentage of the attribute classification with the second-highest frequency from the percentage of the attribute classification with the highest frequency. Similarly, the Total Strength (as a measure of the importance to the customer) can be calculated by:

$$\text{Total Strength} = \frac{\#A + \#M + \#O}{\#A + \#I + \#M + \#O + \#Q + \#R} \tag{1}$$

where "A" stands for attractive, "M" for must-be, "O" for one-dimensional, "I" for indifferent, "Q" for questionable, and "R" for reverse attributes.

The Fong test examines the statistical significance of the attribute classification (Fong, 1996). If the analysis of frequencies results in only marginal differences between the two classifications with the highest frequency, the classification can be tested for statistical significance. The classification is not significant, when

$$|\,a - b\,| < 1.65 \cdot \sqrt{\frac{(a + b) \cdot (2n - a - b)}{2n}} \tag{2}$$

where "a" (and "b") is the classification with the (second) highest frequencies and "n" is the total number of frequencies.

The positive and negative Customer Satisfaction coefficient can be calculated as follows (see, e.g., Baier et al., 2020; Berger et al., 1993):

$$CS+ = \frac{\#A + \#O}{\#A + \#O + \#M + \#I} \text{ with } [1;\ 0] \tag{3}$$

$$CS- = -\frac{\#O + \#M}{\#A + \#O + \#M + \#I} \text{ with } [0; -1] \tag{4}$$

These two coefficients show how fulfilling an attribute can increase (*CS+*) or decrease (*CS-*) customer satisfaction (Berger et al., 1993). A coefficient larger than 0.5 (for *CS+*) or smaller than −0.5 (for *CS-*) indicates that the majority of customers can be positively/negatively affected in terms of their satisfaction (Baier et al., 2020).

At this point, researchers would not be able to know which digital technologies to implement (e.g., based on those classified as attractive, must-be, or one-dimensional) or not (e.g., reverse attributes). Hence, all effort (time, financial resources) to create the survey, acquire responses and analyze the results would be wasted. In contrast, the additional insights from the Dual Response Kano method allows distinguishing more granularly between different types of presumed "indifferent" attributes (as indicated by sub-classifications of previous literature, see Shahin et al., 2017; Yang, 2005).

Accordingly, the adaptive Dual Response question asking whether a digital technology would be rather wanted appeared for 52.44 % of all respondents across all nine technologies (*mean* = 318 respondents out of the total $n = 607$ with $SD = 44.15$). Fig. 4 illustrates for each of the digital technologies whether the technologies were rather wanted (in percentages). It shows that 7 out of 9 (77.77 %) of all digital technologies, which were presumed classified as "indifferent", are actually rather wanted (as opposed to not wanted) by the majority of respondents (> 50 %).

Some digital technologies that were classified as indifferent show a clear indication of not being wanted (e.g., scatter walls) and thus, may represent an indifferent attribute with a tendency towards reverse. However, other indifferent attributes appear to be relatively close to one-dimensional attributes (e.g., e-Wallet payments, additional tables, WiFi, QR codes). Therefore, using the Dual Response Kano method enables uncovering potential "quality attributes" (Yang, 2005) among those previously presumed "indifferent" attributes.

Some of the digital technologies are not only wanted by large shares among those, whose response combination resulted in a classification as "indifferent" (e.g., e-Wallets: 58.2 %; Tablets: 53.1 %; free WiFi: 71.3 %; QR codes: 53.3 %), but also as share of respondents from the total sample (e.g., e-Wallets: 32.1 %; Tablets: 31.5 %; free WiFi: 30.3 %; QR codes: 29.2 %).

One would usually not consider any of these nine digital technologies when just evaluated by the common Kano evaluation as "indifferent". Yet, the Dual Response mechanism shows that the majority of them (i.e., seven) are actually rather wanted by the majority of customers (and thus, potentially important). Since these potentials would otherwise remain hidden as "indifferent", one might consider using a more appropriate naming for these types of attributes. Following Yang's (2005) suggestion to use the term "potential quality" attributes, we refer to these previously hidden attributes that show high potential to change customers' behavior as "latent potentials". Latent potentials are those attributes, which exceed the threshold of 50 % of rather being wanted (and thus, are important for the majority of respondents).

Selecting the threshold of more than 50 % is founded on ensuring that the "majority" (i.e., more than half) wants the related Kano item to be realized. However, 50 % should serve as a general guideline for orientation purposes. Depending on the results (e.g., facing only

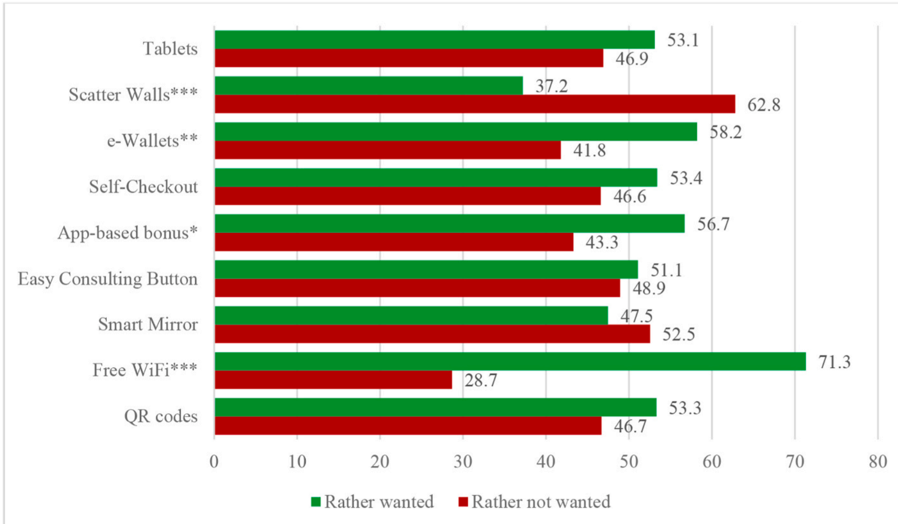

Fig. 4. Respondents' desire for digital technologies presumed as "indifferent" (in %). Note: * = $p < 0.050$; ** = $p < 0.010$; *** = $p < 0.001$ of testing differences within each technology based on χ^2 tests.

Table 2
Two criteria for identifying "latent potential" attributes.

Digital Technologies	Initially "Indifferent"	Indifferent towards Attractive (I_A)	Relative Amount of I_A	Rather wanted (%)	Contrast of desirableness	Probability of being a "latent potential"
Scatter walls	395	20	5.1%	37.2%	–***	Very low/none
Smart mirror	276	16	5.8%	47.5%		Very low/none
In-store tablets	360	22	6.1%	53.1%		Medium to high
Easy Consulting Button	327	24	7.3%	51.1%		Medium to high
QR code at products	332	25	7.5%	53.3%		Medium to high
App-based bonus program	275	22	8.0%	56.7%	+*	Medium to high
Free in-store WiFi	258	25	9.7%	71.3%	+***	Medium to high
e-Wallet payments	335	34	10.1%	58.2%	+**	Very high
Self-service checkouts	307	32	10.4%	53.4%		Very high

"indifferent" attributes, where no attribute yields more than 50 % "wants"), this threshold may be adjusted to allow sensitivity examinations. On the other hand, diluting this threshold too much towards lower percentages may result in assuming that actual indifferent attributes are mistakenly classified as "latent potentials". Therefore, setting this threshold to at least 50 % is recommended. Additional support for selecting 50 % as the threshold, with the intention of comprising the majority, could also be provided by other quality criteria. For instance, the average variance extracted is also set to at least 50 % to have a factor explain the majority of its items' variance (e.g., Brand and Reith, 2022). Similarly, to have constructs explain more than 50 % of an item's variance, factor loadings should be 0.7 or higher, which is calculated by the square root of 50 % ($\sqrt{0.5} = 0.707$; e.g., Brand and Reith, 2022). Moreover, 50 % is also used in Kano studies to graphically show whether the majority of respondents are positively (negatively) affected by an attribute using the "0.5" (or −0.5) score for CS+ (or CS-, respectively; Baier et al., 2020).

To correctly identify "latent potentials", focusing on one criterion (i.e., majority rather wants the item) may be insufficient and offers limited room for sensitivity analysis. Therefore, we extend the conceptual sub-classifications proposed by Shahin et al. (2017) and examined the relative amount of attributes that are "indifferent with a tendency toward attractive" (I_A). Accordingly, differentiating all presumed "indifferent" attributes based on their sub-classifications, the technologies with the highest amount of "indifferent toward attractive" attributes (i.e., e-Wallet payments (34), Self-service checkouts (32), Free in-store WiFi (25), QR code at products (25), Easy Consulting Button (24), In-store tablets (22), App-based bonus program (22)) perfectly mirror the seven "latent potential" attributes.

Hence, the threshold of at least 50 % of respondents rather wanting an item may be complemented by the relative amount of I_A attributes as part of the total number of conventionally presumed "indifferent" attributes. More precisely, when Shahin et al. (2017)'s sub-classification of items reveals more than 6 % of the overall "indifferent" attributes, and, additionally, more than 50 % of respondents indicate a "rather wanted" answer, the probability of identifying a "latent potential" attribute is high (in this study: 100 % correct prediction). Thus, one may recommend combining both criteria (>50 % "rather wanted" and >6 % relative amount of "indifferent toward attractive" (RAIA)) to ensure the correct identification of "latent potentials" (Table 2).

Another indicator for identifying latent potential attributes seems to be significant differences of respondents actually (not) wanting an

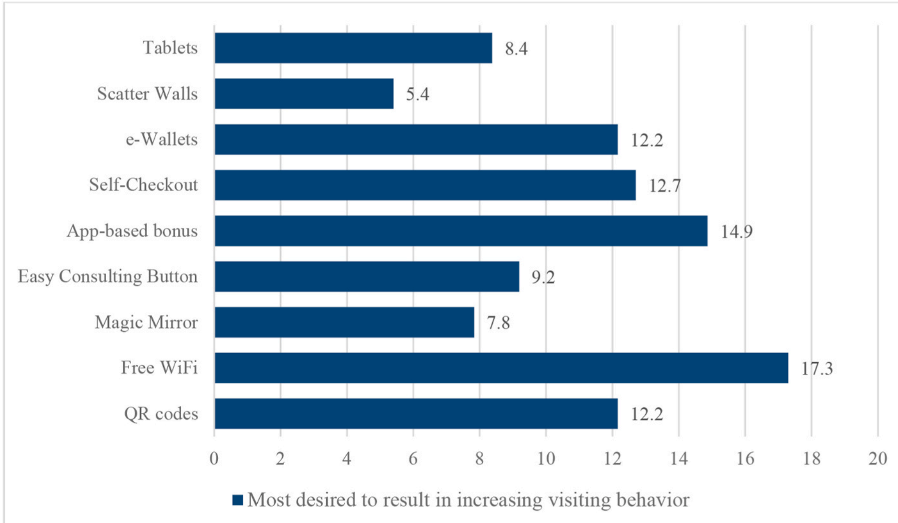

Fig. 5. Digital technologies that are wanted and would result in increasing visiting behavior (in %).

attribute (see Fig. 4). For e-Wallet payments, the App-based bonus program and free in-store WiFi, significantly more consumers rather wanted these technologies than did not want them. These three represent three of the four technologies with the highest RAIA. Confirming this assumption, significantly more respondents did rather not want scatter walls, which are ranked last based on RAIA.

Having multiple digital technologies that used to be classified as “indifferent”, but are actually wanted, results in no clear prioritization of which one to invest in. Accordingly, the second feature of the Dual Response Kano method asks respondents which of the “rather wanted” digital technologies would result in visiting concept stores more often (when applicable) at the end of the survey. This adaptive question was displayed to $n = 370$ respondents (60.96 %).

Free in-store WiFi and the app-based bonus program show the highest share of customers increasing their visits of concept stores among those respondents, whose answer the conventional Kano evaluate as “indifferent”, but who actually rather want them (see Fig. 5). Hence, the Dual Response Kano method not only uncovers attributes previously presumed “indifferent” that are actually wanted by customers, but also allows them to be prioritized based on the share of customers, for whom implementing the most wanted attribute will lead to desired behavior.

Again, some of these presumed “indifferent” technologies leading to increased visiting frequency show large shares not only among respondents, whose answering combination resulted in the “indifferent” classification (e.g., free WiFi: 17.3 %; App-based bonus program: 14.9 %), but also among of the total sample (free WiFi: 10.5 %; App-based bonus program: 9.1 %).

While this article emphasizes the additional insights gained and benefits derived from the Dual Response Kano, one may also limit the focus to those respondents, who primarily welcome new digital technologies. Identifying such more homogeneous sub-segments (e.g., with respondents showing high numbers of technologies classified as “attractive”) can be done using the Segmented Kano approach (Baier et al., 2018). Therefore, we additionally conducted a two-step cluster analysis with automatic detection of the optimal number of clusters based on the Bayesian Information Criterion. This led to a two-segment solution with “Tech-fascinated” respondents (52.22 %; seven technologies classified as attractive and two as indifferent (e-Wallet payment and Scatter walls)) and “Mostly indifferent” respondents (47.78 %; nine

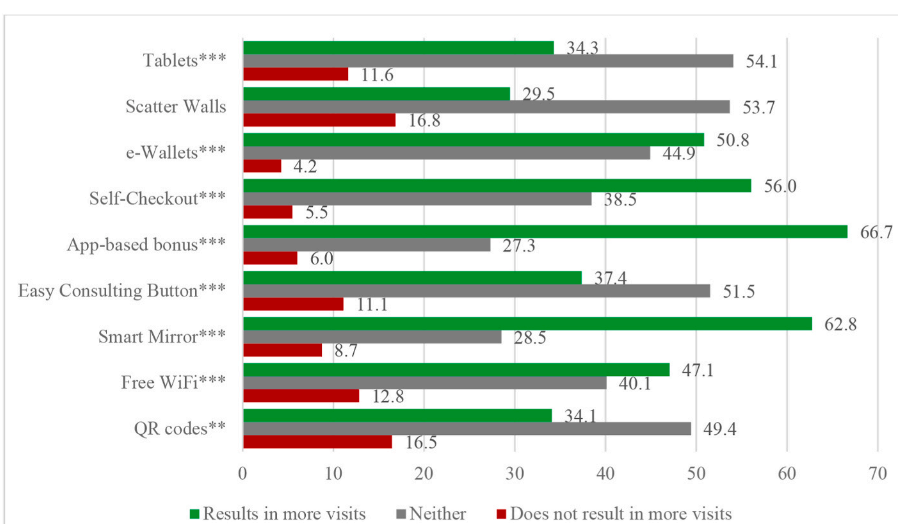

Fig. 6. Attractive attributes and their link to behavior (in %). Note: ** = $p < 0.010$; *** = $p < 0.001$ of testing differences within each technology based on χ^2 tests of “results in more visits” versus “does not result in more visits”.

technologies classified as indifferent; see Appendix C). Although this may help adjust to the needs of the specific sub-segment for whom many attributes are classified as attractive, it comes at the cost of neglecting the rest of the customers/respondents. When interested in uncovering which technology to pursue out of multiple attributes presumed "indifferent" for all respondents/customers, we recommend focusing on the Dual Response Kano.

Finally, the third feature of the Dual Response Kano method allows controlling for the link between (high levels of) satisfaction and behavior(al intention). While the Kano method solely focuses on the relationship between the sufficiency of an attribute and the resulting level of satisfaction (Kano et al., 1984), the original form of this method does not shed light on actual/intended behavior caused by (high levels of) satisfaction. However, even a high level of satisfaction (e.g., for a digital technology) does not necessarily translate into behavior (e.g., increased store visiting frequency), because there might be other drivers that are (more) crucial for causing behavior (e.g., availability of parking lots). Therefore, the third feature of the Dual Response Kano method controls for the link between satisfaction and behavior.

As indicated in Fig. 6, many of the presumed "attractive" attributes do not increase the visiting frequency for concept stores. However, one must distinguish between respondents not using the response "results in more visits" ((passive) absence of visiting behavior) and those indicating "does not result in more visits" ((active) intention not to visit). While the number of consumers, who will not visit the concept stores more frequently, when implementing the corresponding digital technology, is expectably low, the percentage of consumers willing to increase their visiting frequency is remarkably low. Given that this additional question was asked only of respondents, for whom these technologies present "attractive" attributes, one would have expected a much larger share of consumers to change their behavior accordingly.

Except for the app-based bonus program (66.7 %; share of total sample: 23.7 %), smart mirror (62.8 %; share of total sample: 30.8 %), self-checkout (56.0 %; share of total sample: 16.8 %) and e-Wallet payment (50.8 %; share of total sample: 9.9 %), implementing any of the remaining technologies will not necessarily result in an increase in concept store visits for the majority of customers among those who perceived this technology as "attractive" (indicating high satisfaction). In other words, the other digital technologies will not result in more concept store visits for more than half of the respondents, who perceived these technologies as "attractive". For more than half of the nine digital technologies (56 %), the majority of respondents would neither increase nor decrease their visiting frequency when implementing the technology - even though they were perceived as being "attractive".

6. Discussion

6.1. General discussion

In this study, all nine digital technologies were initially classified as indifferent, whereas only free in-store WiFi being re-classified as "attractive" using the evaluation rule by Berger et al. (1993). Therefore, these empirical findings impressively prove the problem identified (i.e., inability to deal with high numbers of indifferent attributes) and appear to be a fruitful setting for demonstrating the advantages of the Dual Response Kano method.

Apart from that, the finding that 100 % of attributes were classified as "indifferent" appears to more remarkable given the more reliable representative sample in this study (inter alia, equal shares between males and females). In contrast, previous Kano investigations employed convenience samples (e.g., Baier et al., 2020; Finn, 2011), and/or small sample sizes (e.g., Chang and Chen, 2014 with $n = 20$; Yang, 2005 with $n = 150$; Gruber et al., 2011 with $n = 272$), where the gender balance may be skewed. Given that males tend to have a higher tech-affinity than their female counterparts (Brand and Reith, 2022), such sample issues could, in turn, skew the number of digital technologies classified as (potentially) indifferent. Therefore, the solution proposed by the Dual Response Kano method may help in numerous cases to prevent researchers/practitioners from being left with no clear indication of many "indifferent" attributes.

As theoretically assumed, but not yet empirically proven, some attributes classified as "indifferent" actually turned out to be potential quality attributes (Yang, 2005) or have a tendency toward being classified as attractive/one-dimensional (Shahin et al., 2017), as indicated by Figs. 4 and 5. In previous empirical endeavors, attributes classified as "indifferent" always ultimately turned out to be "care-free" ones (Yang, 2005) or no attributes were classified as indifferent at all (Shahin et al., 2017). These previous studies also pointed toward the possibility that there are multiple different "indifferent" attributes from a more conceptual perspective and thus called for more granularity for the evaluation table. In contrast, the Dual Response Kano method allows a specific quantification of which attributes are actually wanted and to what extent. As a result, this novel methodological approach allows identifying "latent potential" attributes (i.e., actually wanted by > 50 % of respondents as well as > 6 % RAIA). Moreover, the Dual Response Kano method allows a prioritization, which of the wanted (presumed "indifferent") attributes should be realized first.

Accordingly, multiple attributes that would otherwise be classified as "indifferent" based on the conventional Kano evaluation table are actually wanted by the majority of respondents, thus confirming assumption A1. Similarly, several attributes classified as "attractive" do not actually result in the desired behavior (here: increase store visits), which corroborates assumption A2. Therefore, we align with previous literature that attempts to provide more granular insights into "indifferent" attributes (Shahin et al., 2017; Yang, 2005). Moreover, we extend these endeavors by allowing a specific, precise quantification of actually wanted, formerly presumed "indifferent" attributes as well as a prioritization of which of these wanted attributes should be pursued first.

Concerning the insights gained on how to increase customers' (re-) visiting behavior for concept stores, one needs to distinguish between digital technologies classified as attractive (and their share of the total sample) and those classified as indifferent, but most wanted to result in increased visits (and their share of the total sample). Among the "attractive" digital technologies, the app-based bonus program (share of total sample: 23.7 %) and the smart mirror (share of total sample: 30.8 %) increase store visits the most. While some technologies classified as "indifferent" can also raise consumers' visiting frequency, their share of the total sample is naturally smaller (using free WiFi: 10.5 %; app-based bonus program: 9.1 %).

The reason why many consumers may not have an (active) intention to visit concept stores more often may be that other factors, which are not included in the Kano survey, are more important. For instance, a smart mirror as an "attractive" attribute for someone may lead to high levels of satisfaction in general, but not translates into increased visiting intentions when parking lots are missing or other retailers offer lower prices. When attributes that are classified as "attractive" do not result in the desired behavior, an additional adaptive question may appear in future studies using the Dual Response Kano. This question could ask which other measure could cause the desired behavior instead (or ask for a "why", for instance). Therefore, qualitative insights can be gained that go beyond (measures used in) the actual survey.

6.2. Theoretical contributions

This study contributes to the literature by identifying problems with current Kano studies (i.e., inability to deal with "indifferent" attributes occurring statistically in 36 % of all classifications (Fig. 1), as well as ignorance of the presumed relation between satisfaction and behavior). Then, it provides solutions for these problems, thus, enabling individualized recommendations for consumers with no clear "directions" and learning about their behavioral intentions.

Previous research distinguishes between different types of "indifferent" attributes (e.g., those that are potential quality attributes (Yang, 2005) or those that are closer to attractive/must-be attributes (Shahin et al., 2017)) on a theoretical/conceptual basis. However, researchers were still left with no clear indications of what to do with (different types of) indifferent attributes. Using the Dual Response Kano method, researchers'/practitioners' findings are not limited to attributes clearly classified as attractive, must-be, one-dimensional or reverse, but can also uncover which of the alleged "indifferent" attributes customers want. Moreover, this method not only allows the identification of wanted "indifferent" attributes, but also which one will most likely (i.e., prioritization) result in a specific behavior (e.g., increasing customer visits).

To clarify the currently confusing naming of those attributes that would have been classified as "indifferent", but actually show hidden potential to change the behavior for the majority (i.e., >50 %), we introduce the term "latent potentials". Using this novel terminology makes their true value more evident and differentiates them more clearly from conventional, truly indifferent attributes. Furthermore, this adds to the suggestion by Yang (2005) of a distinction between "care-free" and "potential quality attributes" among "indifferent" attributes (relying on additional importance queries) by enabling to actually measure which indifferent attribute belongs to which classification using the Dual Response mechanism. By introducing this more accurate term, we respond to the call for empirical investigations, which examine terminological inadequacies of the Kano method (Slevitch, 2024). Similarly, the Dual Response adds to the sub-classifications proposed by Shahin et al. (2017) by offering clear measures of how to identify and what to do with presumed "indifferent" attributes. Combining both criteria (>6 % RAIA and >50 % rather wanted shares), researchers/practitioners receive clear implications on how to identify "latent potential" attributes, which were previously overlooked as just being "indifferent" attributes. In particular, the newly introduced "latent potentials" seem to mirror similar aspects captured by the sub-classification I_A (Shahin et al., 2017). However, additional future studies should critically reflect on the 6 % threshold for the RAIA criterion. Since this is the first application of the Dual Response Kano, more reliability for this criterion would be welcomed.

Previous literature showed that many attributes are classified as indifferent (e.g., Baier and Rese (2020): 68 %; Rese et al. (2019): 40 %; Stöcker et al. (2021): 90 %; 36 %; 22 %), which leaves researchers/practitioners without any clear implications (after investing time/money to obtain such "insights"). However, the Dual Response Kano method allows researchers/practitioners to solve this problem. More precisely, it allows them to (i) identify those "indifferent" attributes that are actually wanted by customers, as well as (ii) which of the wanted attributes are most wanted and (iii) will result in corresponding behavior.

Furthermore, the Dual Response Kano method contributes to the literature by making it possible to control for (intended) behavior, instead of focusing only on satisfaction. As shown by the empirical study, attributes classified as "attractive" (high satisfaction) do not necessarily translate into behavior. Hence, the Dual Response Kano method empirically uncovers that the presumed assumption of the Kano method (high satisfaction leads to desired behavior) does not always apply. This novel method allows controlling for the number of customers, who will actually change their behavior based on high satisfaction levels. Additionally, this takes into account that attributes not included in the survey may be more important in driving behavior (e.g., parking lots near the store compared with digital technologies). By including the control variable of the Dual Response Kano method, researchers receive additional insights into whether the attributes investigated are sufficient to cause behavior(al changes). Besides, this study responds to the call for research employing additional performance metrics juxtaposed with customer satisfaction (Baier and Rese, 2020). Previous Kano surveys detected a bias stemming from the exclusion of additional parameters (Finn, 2011). Applying the Dual Response Kano method can attenuate this bias, as the method captures not only respondents' satisfaction with attributes, but also the related behavior.

Similarly, an additional extension of the Dual Response Kano method may allow researchers receiving in-depth insights into which (of the attractive) attributes will result in a certain behavior by adding an open-ended question when asking about which attractive attribute is most likely to cause behavior. When asking about which of the attributes classified as attractive will or will not result in a certain behavior, an additional display logic could ask what other features/reasons could cause a behavior beyond the attributes covered in the questionnaire (when selecting the answer for not resulting in a certain behavior). This approach allows (i) overcoming the restriction on attributes used in the survey and (ii) enables contextualization to other important reasons for a behavior. For instance, respondents who indicate that smart mirrors will not result in more store visits will receive an additional, adaptive question asking which reason would result in more store visits.

While machine learning based refinements to the Kano method offer helpful information (e.g., Zhao et al., 2024), the survey-based approach used for the Dual Response Kano allows to examine novel, innovative features that may be implemented in the future but are not established yet. For applying machine learning in Kano studies, large datasets are needed. Therefore, these approaches often rely on online customer reviews of sold products (e.g., Bi et al., 2019; Kim et al., 2025; Zhao et al., 2024). In contrast to these approaches, the survey-based Dual Response Kano method is not limited to products/solutions that already exist. Hence, the Dual Response Kano also provides a cost-efficient way to analyze consumers' satisfaction and their (intended) behavior for innovative features. Besides, additional insights can be gained that are beyond conventional Kano results (from machine learning refinements), when implementing the adaptive feature concerning the qualitative question into the survey. Furthermore, using representative samples for an online survey helps overcome the self-selection bias inherent to online customer reviews (i.e., tendency that rather very satisfied and very unsatisfied are most likely to write reviews; see also Baier et al., 2025). Compared with machine learning refinements based on online reviews, the Dual Response Kano also allows covering all features of interest instead of the main one/two aspects covered in reviews (resulting in an incompleteness problem of online reviews (Baier et al., 2025)).

In addition, this article contributes to the literature by outlining which digital technologies can help (small retailers and) concept stores, particularly to increase consumers' visiting frequency. More precisely, an app-based bonus program (66.7 %) and smart mirrors (62.8 %) are most likely to increase visiting frequency among all attributes ranked as "attractive" (Fig. 6). Since the adaptive questions are only shown to some respondents (based on their answer combinations), it is necessary to also control for the share of respondents changing their behavior in comparison to the total sample (app-based bonus program: 23.7 %; smart mirror: 30.8 %). Additionally, these insights respond to the call to examine how technologies can affect consumers' behavior in retail settings (Plangger et al., 2022).

6.3. Limitations

While the Dual Response Kano method enables overcoming two major shortcomings of the initial method, this initial study is bound by some limitations. First and foremost, since this is the first and only application of the Dual Response Kano method, it cannot be taken for granted that the valuable additional information provided by this approach will be as insightful in other empirical applications (reliability). However, given that 36 % of all Kano classifications lead to attributes being classified as "indifferent" and based on empirical examination of extant Kano studies, attributes seem to be classified as indifferent relatively often.

Similarly, this study controls for behavioral intention for attributes classified as "attractive". Future studies may extend this adaptive question by not only controlling for behavioral intention, but also identifying which alternatives would result in this behavior in case the feature is assigned as "not resulting in the intended behavior". For example, smart mirrors are classified as "attractive" and the adaptive question asks whether using this technology will result in increased visiting behavior. When respondents negate this question, an additional adaptive question could ask which other factor could result in increased visiting behavior using a free-text question. This way, qualitative insights can also be gained beyond the attributes selected for the survey. We strongly encourage future research to add this additional adaptive feature to the Dual Response Kano to uncover which factors are truly causing the desired behavior, even if the items used in the survey may not be sufficient to trigger this behavior.

Additionally, it must be considered that while intention and behavior are correlated, often intention does not translate into behavior (Brand, 2025). Therefore, the attributes leading to the desired behavior according to the survey might not actually turn into visiting behavior if they are put into practice. In addition, longitudinal designs to track changing perceptions of "indifferent" attributes, following Nilsson-Witell and Fundin (2005), or cross-cultural validation (Brand and Reith, 2022) would be of interest. While our classification of "latent potentials" was inspired by those of Yang (2005) and Shahin et al. (2017), one may additionally inquire into the importance of the attributes to allow a more direct comparison with Yang's (2005) results.

Next, this study is limited to the case of offline shopping. In contrast, for online shopping, clickstream data is available and thus, allows insightful analysis of customers' needs without using surveys (Rausch and Brand, 2022). However, for innovative features that cannot yet be or are not yet implemented in stores/companies, the Dual Response Kano method will remain an important tool to analyze customers' needs with low costs (before actually implementing them). Relatedly, while the data collection took place four years ago and thus, limits the timeliness concerning the technologies, the main focus of this article is about the methodological advancement.

Finally, this investigation aligns with the typical Kano questions when it comes to operationalizing (visiting) intention (i.e., asking only one question and offering a handful of response options). Instead, one could consider incorporating constructs with item batteries that would be answered on a Likert-scale. More granular estimations of respondents' behavioral intention could be measured compared with just three options "results in more visits", "neither, nor", and "does not result in more visits". However, indicating such responses for, say, a three-item battery for each digital technology would easily result in an excessive number of questions (e.g., three items for ten technologies already results in 30 questions on top of the 20 regular Kano questions (both functional and dysfunctional question)). Similarly, we used "rather wanted" or "rather not wanted" (i.e., binary approach) as response options for the adaptive Dual Response feature to enable a straightforward decision that helps practitioners decide what to do. However, future studies may consider using more granular response options (e.g., 5-point Likert scale) even though this might cause ambiguity about whether items are really wanted (and thus, does not solve the problem initially identified).

6.4. Practical implications

Using the Dual Response Kano, practitioners are not left without clear implications when facing attributes classified as "indifferent" (which appears to happen frequently). Instead, this new methodological approach allows for clear implications of what (not) to do with such attributes. This seems to be particularly helpful given the high prevalence of attributes classified as "indifferent". By using the Dual Response Kano, practitioners may avoid investing time and money in surveys that would leave their questions about which technology to implement unanswered. Moreover, when using the discussed additional feature of asking respondents which factor would result in a certain behavior when an attractive attribute is selected as "not resulting in the desired behavior", further qualitative insights can be gained.

Given the technically easy implementation of the adaptive features in the Dual Response Kano (i.e., using display logics), basically every practitioner who has access to (online) survey software can take advantage of this methodological advancement. Similarly, analyzing the related results is relatively easy, as it focuses on the relative frequencies of the answers provided (e.g., percentages of respondents indicating a presumed "indifferent" item is actually wanted).

To enable an easy-to-use "how-to" for employing the Dual Response Kano, we briefly summarize its three steps. First, after implementing the two regular Kano questions (functional and dysfunctional one), the first adaptive feature is added (see also Fig. 2). For this feature, a display logic will adaptively show one additional question for each item after the two regular questions. This question appears in cases where the responses to the functional and the dysfunctional would lead to a classification as "indifferent" (see Fig. 1). It asks whether the corresponding item/measure in general is rather wanted or not (offering these two response options). Second, after answering the Kano questions for all items, another display-logic is implemented. This adaptive question appears when at least two items were categorized as ("indifferent", but selected to be) "rather wanted". Accordingly, respondents are asked to choose the one item that they want most in order to result in a certain behavior (e.g., increase shopping frequency). As response options, all items that were selected as "rather wanted" are listed. Third, after selecting the most wanted item, one last adaptive question may appear. This question pops up when at least one item was classified as "attractive" (again, using a display-logic). Respondents are then asked to indicate for all those items categorized as "attractive" (if any) to what extent these items will result in a certain behavior. For instance, the response options could be "results in increased visiting frequency of concept stores", "nor neither", "does not result in increased visiting frequency of concept stores". In addition to these three steps, one may also consider the before-mentioned adaptive feature for qualitative insights. For instance, if an item categorized as "attractive" would still not result in increased visiting intentions, one may ask either why this is the case or directly ask which other item would increase their visiting intentions (using an open-ended question).

Additionally, practitioners will be able to clearly select those attributes that will result in a certain behavior for most of their customers using the Dual Response method (for indifferent and attractive attributes). Since the Dual Response Kano identifies not only actually wanted items (here: technologies), but also which of the desired items is wanted most, a clear prioritization helps companies to select the right measure. Therefore, store owners will be prevented from making misinvestments by identifying those attributes that, on the one hand, increase customers' satisfaction, but will not result in beneficial behavior on the other hand.

Furthermore, the Dual Response Kano can help brick-and-mortar retailers reposition their tech-strategy, which also helped some stores, e.g., Walmart and Target, during the pandemic (Sheth, 2021). Since stationary retailing is still a popular option in post-pandemic times (Rese and Wolfschmidt, 2024), the Dual Response Kano can support retailers in investigating new approaches to attract customers to physical stores (Breugelmans et al., 2023).

CRediT authorship contribution statement

Benedikt M. Brand: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexandra Rese:** Writing – review & editing.

Funding

There was no funding involved in the investigations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank Sarah Abels, Maya Barkan, Alexandra Mann, and Nele Mitsdoerffer for their support in setting up the survey. Moreover, the authors thank the Chair for Marketing & Innovation at the University of Bayreuth (Prof. Dr. Daniel Baier) for financing the panel used to acquire the representative sample.

Appendix A. Previous milestones in the development of the Kano method

Phase	Author (Year)	Milestone(s) reached
Emergence (1984–1999)	Kano et al. (1984)	First publication on the Kano model (Theory of Attractive Quality) and the Kano method
	Berger et al. (1993)	Development of evaluation rules and modified graphical illustration of results; adjustments for the response options; development of the evaluation rule "M > O > A > I"
	Lee and Newcomb (1997)	Development of the Category Strength and Total Strength metrics (with related graphical illustration)
	Matzler and Hinterhuber (1998)	Empirical investigation of the combination of the Kano method with the Quality Function Deployment method
Exploration (2000–2011)	Kano (2001)	Investigation of the dynamic process of successful quality attributes
	Matzler and Sauerwein (2002)	Integration of techniques for classifying quality attributes (penalty-reward-contrast analysis, importance grid, critical incident technique, analysis of complaints and compliments)
	Nilsson-Witell and Fundin (2005)	Optimization of validity of the Kano method based on adjusted wordings of the response options
	Yang (2005)	Integration of attributes' importance and extension of the Kano categories A, O, M, I into sub-categories (highly attractive/less attractive, high value-added/low value-added, critical/necessary, and potential/care-free)
	Löfgren et al. (2011)	Identification of three life cycles of quality attributes; investigation of the life cycle of quality attributes
	Gruber et al. (2011)	Examination of potential intercultural differences of the Kano method
	Högström (2011)	Adjustments for the questions and answering options of the Kano method. Proposition of a new evaluation table.
Refinement (2012–2022)	Shahin et al. (2013, 2017)	Proposition of an optimized Kano model that adjusts the curves of the Kano model. Extension of the evaluation table with additional sub-categories for reverse, attractive, and must-be attributes. Two of the nine indifferent attributes are re-categorized as questionable. Differentiation of the seven remaining "indifferent" attributes into four sub-categories (indifferent, indifferent towards A, M, O, indifferent towards reverse A, O, M). Revision of the satisfaction coefficients.
	Chang and Chen (2014)	Modification of the satisfaction coefficients.
	Xiao et al. (2016)	Integration of online customer reviews for attribute identification; definition of attribute classification conditions with regard to the Kano categories; proposition of the marginal effect-based Kano model (MEKM)
	Baier et al. (2018)	Development of a Segmented Kano approach that combines the Kano method with a simultaneous cluster analysis (e.g., of customer segments and use-case groups)
	Song (2018)	Proposition of a new paired approach (better–worse questions) with a five-point ordinal scale, and a Satisfaction/Dissatisfaction Index. Extension of the O, A, M categories into sub-categories
	Bi et al. (2019)	Development of a categorization approach based on customer reviews and customer satisfaction dimensions
	Vaez-Shahrestani et al. (2020)	Addition of sub-categories for one-dimensional attributes (trending toward must-be/attractive or primarily one-dimensional)
	Potra et al. (2022)	Integration of computer-assisted human behavior tools for biometric measurements (e.g., eye tracking, galvanic skin response)

Appendix B. Socio-demographic information and descriptive statistics

	Counts	Relative Proportion (in %)
Averaged age	32 years old (*SD* = 5.47)	
Gender	Female: 313	Female: 51.6 %
	Male: 294	Male: 48.4 %
Education	w/o school-leaving qualification: 13	w/o school-leaving qualification: 2.1 %
	Primary education: 44	Primary education: 7.2 %
	Secondary School level: 190	Secondary School level: 31.3 %
	High School degree: 128	High School degree: 21.2 %
	Technical diploma: 45	Technical diploma: 7.4 %
	University degree: 172	University degree: 28.3 %
	PhD: 9	PhD: 1.5 %
	Other: 6	Other: 1.0 %
Occupation	Pupil/trainee: 16	Pupil/trainee: 2.6 %
	Student: 68	Student: 11.2 %
	Employed: 422	Employed: 69.5 %
	Unemployed: 58	Unemployed: 9.6 %
	Retired: 14	Retired: 2.3 %
	Other occupation types: 29	Other occupation types: 4.8 %
Net income (per month)	≤500€: 34	≤500€: 5.6 %
	501-999€: 49	501-999€: 8.1 %
	1000–1999€: 181	1000–1999€: 29.8 %
	2000–2999€: 173	2000–2999€: 28.5 %
	3000–3999€: 77	3000–3999€: 12.7 %
	≥4000€: 77 no information: 36	≥4000€: 9.4 % no information: 5.9 %

(*continued on next page*)

(*continued*)

	Counts	Relative Proportion (in %)
Residence	<2000 inhabitants: 80 2000–4999 inhabitants: 49 5000–19,999 inhabitants: 110 20,000–99,999 inhabitants: 164 100,000–999,999 inhabitants: 143 ≥1,000,000 inhabitants: 59 no information: 2	<2000 inhabitants: 13.2 % 2000–4999 inhabitants: 8.1 % 5000–19,999 inhabitants: 18.1 % 20,000–99,999 inhabitants: 27.0 % 100,000–999,999 inhabitants: 23.6 % ≥1,000,000 inhabitants: 9.7 % no information: 0.3 %
Visiting frequency of concept stores *before* the pandemic	Never: 288 1 per year: 113 1 per month: 137 1 per week: 45 Daily: 24	Never: 47.4 % 1 per year: 18.6 % 1 per month: 22.6 % 1 per week: 7.4 % Daily: 4.0 %
Attitude towards concept stores	4.01 (*SD* = 1.01) on a 5-point scale from 1 = very negative to 5 = very positive	
Innovativeness	3.18 (*SD* = 0.73) on a 5-point Likert Scale from 1 = completely disagree to 5 = completely agree	

Appendix C. Segmented Kano results

	Segment 1 ("Tech-fascinated")	Segment 2 ("Mostly indifferent")
Average age	31.37 (*SD* = 5.44)	32.25 (*SD* = 5.46)
Gender (%)	Female: 52.7 Male: 47.3	Female: 50.3 Male: 49.7
Education (%)	w/o school-leaving qualification: 2.5 Primary education: 6.3 Secondary School level: 28.7 High School degree: 8.8 Technical diploma: 22.7 University degree: 28.1 PhD: 1.6 Other: 1.3	w/o school-leaving qualification: 1.7 Primary education: 8.3 Secondary School level: 34.1 High School degree: 5.9 Technical diploma: 19.3 University degree: 28.6 PhD: 1.4 Other: 0.7
Occupation (%)	Pupil/trainee: 2.8 Student: 13.6 Employed: 69.1 Unemployed: 8.2 Retired: 1.9 Other occupation types: 4.4	Pupil/trainee: 2.4 Student: 8.6 Employed: 70.0 Unemployed: 11.0 Retired: 2.8 Other occupation types: 5.2
Net income (%)	≤500€: 5.7 501-999€: 7.3 1000–1999€: 29.3 2000–2999€: 27.4 3000–3999€: 15.5 ≥4000€: 9.1 no information: 5.7	≤500€: 5.5 501-999€: 9.0 1000–1999€: 30.3 2000–2999€: 29.7 3000–3999€: 9.7 ≥4000€: 9.7 no information: 6.2
Residence (%)	<2000 inhabitants: 12.3 2000–4999 inhabitants: 7.3 5000–19,999 inhabitants: 19.9 20,000–99,999 inhabitants: 27.1 100,000–999,999 inhabitants: 22.7 ≥1,000,000 inhabitants: 10.7 no information: 0	<2000 inhabitants: 14.1 2000–4999 inhabitants: 9.0 5000–19,999 inhabitants: 16.2 20,000–99,999 inhabitants: 26.9 100,000–999,999 inhabitants: 24.5 ≥1,000,000 inhabitants: 8.6 no information: 0.7
Visiting frequency of concept stores *before* the pandemic	Never: 42.6 1 per year: 19.6 1 per month: 24.6 1 per week: 8.2 Daily: 5.0	Never: 52.8 1 per year: 17.6 1 per month: 20.3 1 per week: 6.6 Daily: 2.8
Attitude towards concept stores	4.28 (*SD* = 1.01)	3.72 (*SD* = 1.12)
Innovativeness	3.36 (*SD* = 0.75)	2.98 (*SD* = 0.65)

Data availability

Data will be made available on request.

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