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"Beyond liking" measures in food-related consumer research supplement hedonic responses and improve ability to predict consumption

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ABSTRACT

Sensory and consumer science is concerned with measuring perceptual and affective responses to consumer products. Historically, hedonic responses (degree of liking or preference for a set of test products) have been the primary measure of product performance in food-related consumer research, but recent years have seen an increase in the uptake of perceptual measures that go "beyond liking", with interest primarily focusing on product-elicited emotions, conceptualisations and situational appropriateness. Although the ultimate purpose of collecting such responses is that they are predictive of what consumers will like, choose and consume in their everyday life, such data are very rarely validated against actual consumer behaviour.

Against this backdrop, the present research aimed to evaluate the ability of emotional, conceptual, and situational appropriateness responses to predict a behaviourally relevant measure of product performance – frequency of past consumption. Two (online) consumer studies were conducted with US adults, using salads (Study 1, n = 606) and non-alcoholic beverages (Study 2, n = 603) as product categories. In each study, the predictive ability of each set of measures was benchmarked against that of expected liking to identify the optimal (most predictive of consumption) combination of product-related measures.

Both studies provided evidence that all included measures (liking, emotional, conceptual, and situational responses) were significantly correlated with frequency of past consumption, and importantly, that inclusion of "beyond liking" measures improved behavioural prediction over and above models based on hedonic responses only. These findings confirmed that liking in and of itself is insufficient as a predictor of consumption and supported calls for the purposeful combination of different response types using "global" or multi-response approaches. Differences between the two studies pertaining to the relative importance of liking and the best combination of predictors were uncovered, suggesting that the optimal combination of "beyond liking" measures in practical applications is likely to be study-specific.

1. Introduction

1.1. "Beyond liking" measures in food-related consumer research

Sensory and consumer science is concerned with measuring perceptual and affective responses to food and beverage products (Tuorila & Monteleone, 2009). Although the very idea of collecting such responses is that they are predictive of what consumers will like, choose and consume in their everyday life, such data are very rarely validated against actual consumer behaviour. Understanding the potential of sensory and consumer data to predict consumption would increase the relevance of the field as a whole at a time when consumers are urgently requested to modify their dietary habits for public health and environmental reasons (Willett et al., 2019). It also seems a timely issue to consider since, due to blurring disciplinary boundaries, perceptual measures routinely collected in sensory and consumer studies are now more numerous and more diverse than ever before (Jaeger, Jin, Hunter, Roigard, & Hedderley, 2020; Meiselman, 2013; Spinelli et al., 2019). It is also of clear interest in commercial R&D, as the success rate for new products in food and other consumer packaged goods is notoriously low (Dijksterhuis, 2016), making measures of product performance that effectively predict consumer choices in the marketplace highly sought

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after.

Historically, hedonic responses (degree of liking or preference for a set of test products) have been the primary measure of product performance in the food and beverage (F&B) industry, particularly in the context of new product development and line extensions (Giacalone, 2018). This makes sense in light of everyday experience (people eat what they like), and combine with experimental evidence that liking, in controlled conditions such a sensory testing facility is a fairly good predictor of product acceptance and consumption (Hellemann & Tuorila, 1991; Sidel et al., 1972; Vickers & Mullan, 1997; Vickers, Mullan & Holton, 1999).

Nonetheless, liking ratings are, in and of themselves, poor predictors of consumer choices (Cardello, Schutz, Snow, & Lesher, 2000; Köster & Mojet, 2007), especially when comparing products of similar and high sensory quality (Rosas-Nexticapa, Angulo, & O'Mahony, 2005). This limitation has prompted sensory and consumer scientists to take an interest in performance measures that go "beyond liking," with interest primarily focusing on product-elicited emotions and conceptualisations and situational appropriateness.

Emotion research has gained widespread popularity in product-focused research (e.g., Meiselman, 2021), driven by the interest in understanding the influences that consuming food and beverages have on people's mood and emotions (Köster & Mojet, 2015). Reasoning that purchase decisions for F&B products are seldom driven exclusively by rational considerations, emotion researchers seek to understand how intrinsic and extrinsic aspects of F&Bs relate to the emotions experienced during consumption so that new products can be designed to deliver the desired emotional benefits. While some authors argue in favour of physiological methods in emotion research that do not rely on verbal expression (e.g., heart rate, brain responses, skin conductance), at present questionnaires remain the *de facto* standard approach for measuring product-elicited emotional associations (Cardello & Jaeger, 2021a). These comprise emotion words that span the two core dimensions of human affect – valence, arousal – and sometimes also dominance. Some questionnaires are further adapted to be product specific (Cardello & Jaeger, 2021b).

Product conceptualisations also seek to describe products. Questionnaires are again the dominant approach and can include emotional words but always extend beyond these (e.g., classy, genuine, conservative, free-spirited, youthful) (e.g., Thomson, 2016; Thomson and Coates, 2021). Thus, there can be some overlap with emotion research, especially when emotions are conceptualised as product-elicited associations. While applications have been modest relative to emotions research, product conceptualisations have also been shown to be a rich source of product insight (e.g., Jaeger & Giacalone, 2021; Ng, Chaya, & Hort, 2013).

Consumption context and its role in orienting consumers' choices is of considerable importance (Cardello & Schutz, 1996), and it is generally assumed that products are chosen to fulfil the goals associated with a particular consumption situation (Giacalone and Jaeger, 2019a). Accordingly, there has also been a steady stream of research focused on situational appropriateness – defined as degree of fit between products and intended usage situations as perceived by the consumer (Schutz, 1988) – specifically as an adjunct to hedonic tests, with the end-goal of ensuring that new products have not only high acceptability, but also high appropriateness for the consumption contexts normally associated with that category. Situational appropriateness data are relevant for differentiating between a wide variety of product categories (Giacalone, 2019) and are considered essential for full product characterisation (Cardello & Schutz, 1996; Jaeger & Porcherot, 2017).

1.2. Research aims and expected findings

Despite enthusiasm for and uptake of "beyond liking" measures, there has been a tendency toward using these measures in isolation. For instance, studies that consider situational appropriateness often view this as an adjunct to hedonic responses, but rarely discuss connections to emotions, conceptualisations or cognitions (Jaeger, Jin, et al., 2020; Jaeger, Roigard et al., 2020). Similarly, much product-focused emotion research serves as an adjunct to hedonic responses (e.g., King & Meiselman, 2010, Schouteten et al., 2015, Spinelli & Monteleone, 2018). Yet, reliance on a single measure of product performance – be it liking, emotional associations or situational appropriateness – is unlikely to comprehensively capture consumers' F&B experiences. For this reason, the purposeful combination of multiple types of product responses - liking, emotional, conceptual, situational and/or attitudinal – has appeal to better capture consumer experiences (e.g., Jaeger, Jin et al., 2020; Spinelli et al., 2019).

To support their uptake, we focus the present research on the question of how to construct these "global" or multi-response approaches such that "beyond liking" measures combine with liking (or other affective responses) in a way that is meaningful and efficient. Moreover, although such measures purportedly provide additional insights and in theory better understanding of food-related consumer behaviour, empirical evidence supporting this notion has not been published in the literature[1].

While there is little doubt that preferences, *all else being equal*, are key determinants of food acceptance and consumption, we lack a clear understanding of the behavioural correlates of e.g., product-related emotions or appropriateness ratings. Some emotions, such as boredom, have been linked to product rejection both theoretically and experimentally (Sulmont-Rossé, Chabanet, Issanchou, & Köster, 2008), but in most cases the relationship between food-elicited emotions and consumer behaviour is not clear-cut (Giacalone, 2018). Situational appropriateness has been linked to food choice and consumption frequency but only in a few studies (Giacalone & Jaeger, 2019a,b; Sosa et al., 2005).

There is, therefore, a need for studies to consider different measures, in combination with one another and with liking, to better understand their predictive value (over and above that of liking alone) with respect to behaviourally relevant measures such as frequency of consumption and purchase.

Against this backdrop, the present research aimed to evaluate the ability of emotional, conceptual, and situational appropriateness responses to predict frequency of past consumption in two different product categories. Although focusing on past consumption may seem counter-intuitive, since we ultimately want to understand and predict *future* behaviour, it should be noted that for common food and beverage products previous behaviour is usually a very good predictor of future consumption, and generally outperforms attitudinal measures such as purchase intention (e.g., de Vries et al., 2014; Honkanen, Olsen, & Verplanken, 2005; Wong & Mullan, 2009).

Focus was directed to three expected findings (EF) which needed to be confirmed to support "beyond liking" measures and illuminate their importance in food-related consumer research. Fig. 1 provides a visual representation of the framework and expected findings (EF) where EF1 and EF2 directly build on the above literature.

In terms of theoretical underpinnings, EF3 relates to studies on emotion measurement in sensory and consumer science that indicate that many emotion terms have an intrinsic hedonic value (Prescott, 2017), and accordingly, several studies have found that, when applying dimension reduction techniques to emotional data, one (often the first) of the resulting dimensions can be interpreted as separating products in terms of liking-disliking (whereas the other dimension is most often explained in terms of arousal, see e.g., Jaeger, Spinelli, Ares, & Monteleone, 2018; Jaeger et al., 2020a). A similar reasoning can be applied to conceptualizations, and although methodological research for this

[1] This sentence refers to the *scientific* literature. Fast moving consumer goods (FMCG) companies almost certainly own relevant datasets linking product-related measures to market performance, which are not publicly available for obvious reasons.

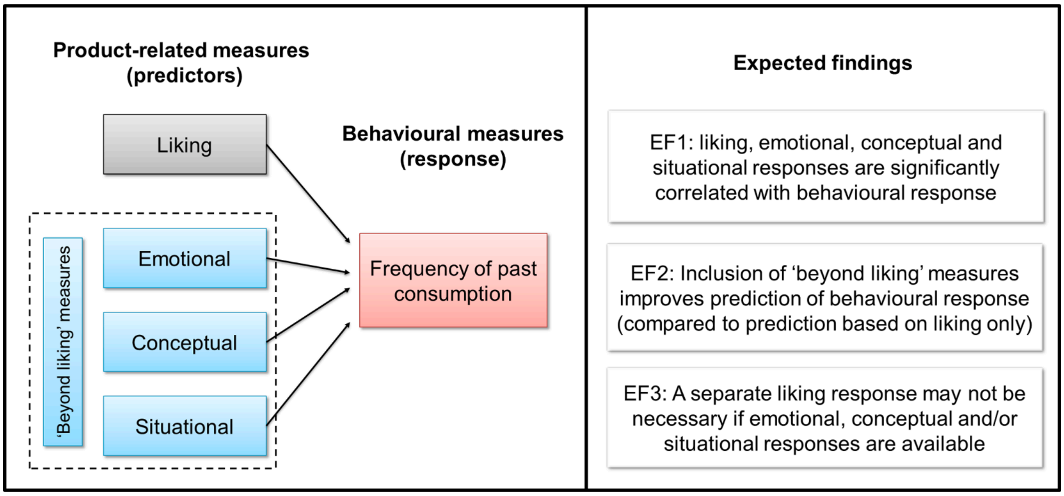

Fig. 1. Framework and expected findings.

type of data is limited it can be assumed that they too overlap with liking since many of these terms also appear hedonically valenced (e.g., "arrogant", "pretentious", "happy", "comforting"). The relationship between situational appropriateness and liking is also interesting. In general, research shows that liking and appropriateness are always going to be somewhat correlated; however, the strength of the relationship depends on the level of liking and the degree of liking differences between the samples. Specifically, appropriateness and liking have been found to be highly correlated for disliked products, and/or when differences in liking between the products are substantial (Jaeger et al., 2019, 2021), whereas the two tend to carry different information when samples that are similarly liked and liked in absolute (Giacalone & Jaeger, 2019b). The reasoning behind EF3 is, thus, that if "beyond liking" measures also capture hedonic responses, a separate liking response may not be necessary to predict behavioural responses. This is an interesting proposition, and would have considerable potential impact if confirmed, because it challenges the implicit notion that "beyond liking" means that liking, in itself, is not enough, rather than the fact that liking may not be needed at all.

Empirically, we conducted two consumer studies pertaining to salads (Study 1) and non-alcoholic beverages (Study 2). Both were conducted as online surveys using product names as written stimuli, with expected liking as the response variable for liking and frequency of past consumption as the behavioural response. Below, the full details relating to the empirical approach are given, followed by results and discussion.

2. Materials and methods

2.1. Participants

The research was conducted in the USA (full geographical coverage) with 1209 adult consumers (18–65 years old, 50% women) with varying backgrounds (ethnic, socio-economic, political, etc.). Participants were randomly assigned to Study 1 (Salads, n = 606) or Study 2 (Beverages, n = 603)[2]. Part 1 of Supplementary Material has full participant details by study.

Participants were registered with an ISO-accredited web panel provider. All were free of major dietary restrictions and allergies; all were involved in at least some of the household grocery shopping.

The research was covered by a general approval for sensory and consumer research from The Human Ethics Committee at the New Zealand Institute for Plant and Food Research Limited. Participants were informed that their responses would be confidential, and voluntarily agreed to take part.

2.2. Product stimuli

The product categories in Study 1 and Study 2 were salads and non-alcoholic beverages, respectively. These were appropriate case studies, being long established product categories in continued evolution (Vidal, Ares, & Gimenez, 2013; Jaeger & Giacalone, 2021). The inclusion of two case studies, one focusing on solid foods and the other on beverages, helped to increase the generalizability of the findings. Salads and non-alcoholic beverages were chosen as case studies as they are established product categories in which a range of variation with respect to liking, emotion, conceptual and appropriateness could be covered.

Written stimuli were used deliberately to direct participants' attention beyond sensory acceptability, which facilitated achievement of the aims of the research, as well as in keeping with the fact that the studies were conducted online.

An iterative process took place where candidate product names within each product category (salads and non-alcoholic beverages) were initially suggested by the authors and revised following discussion with five experienced sensory and consumer research professionals from the USA. This resulted in a total of nine product names included in each study: Study 1) *Caesar salad, Caesar salad with chicken, Cobb salad, Coleslaw, Coleslaw (vegan mayonnaise), Mixed greens salad, Mixed greens salad with tuna, Pasta salad, Pasta salad with beef*; and Study 2) *Cow's milk, Energy drink, Fruit smoothie, Fruit smoothie with soy milk, Iced coffee, Iced coffee with almond milk, Kombucha, Oat milk, Still water*.

The selection strategy was partly informed by concurrent product-focused research investigations (see Jaeger & Giacalone, 2021). Some of the stimuli were paired and represented regular and plant-based variants of the same "base product": for example, Caesar salad and Caesar salad with chicken in Study 1, and Cow's milk and Oat milk in Study 2, whereas the remaining stimuli were chosen to obtain category coverage and to span variation regarding familiarity. Finally, variation regarding emotional, conceptual, and situational product characteristics was sought across the salads and beverage stimuli with inspiration from the existing literature on these product categories (e.g., Ng, Chaya, Hort, 2013; Waehrens, Grønbeck, Olsen, & Byrne, 2018; Samant & Seo, 2020; Vidal et al., 2013).

[2] Data co-use disclosure statement: some of the data for Study 2 (beverages) are also used in: Jaeger, S. R., & Giacalone, D. (2021) [Fd. Res. Intl., 144, 110363], but with a focus on product characterisation and not behavioural prediction.

2.3. Response variables

Emotional associations (Table 1a): The circumplex-inspired emotion questionnaire with 12 pairs of emotion words was used (Jaeger, Roigard et al., 2020b). Prior to initiating stimuli evaluation, the circular structure of the questionnaire was described to participants, identifying the two underpinning dimensions – valence (pleasure to displeasure) and arousal (activation to deactivation) – and how combine to the 12 axes that feature in the questionnaire (Part 2 of Supplementary Material). The instructions closely resembled those given, in a CLT context, in Jaeger, Roigard et al. (2020b). Participants were instructed to think about [salad/beverage name] and select one word pair in response to the prompt "how do you feel?"

Conceptual associations (Table 1b): The list of 30 words developed by Thomson (2016) was implemented as a CATA (check-all-that-apply) question. Participants were instructed to think about [salad/beverage name] and select all applicable words.

Situational appropriateness (Table 1c): Ten usage situations were selected to span a range of perceived situational appropriateness for the stimuli (specific to product category). Participants were instructed to think about [salad/beverage name] rate the use situations on 7-point scales (1='not at all appropriate'; 7='very appropriate').

Expected liking: The statement "I expect to like this [salad/beverage name]" was used and responses obtained on a 7-point Likert scale (1='disagree strongly'; 7='agree strongly'). This measure was used for parsimony in data collection since additional Likert statements were used, relating to familiarity, consumption and purchase. Directed by the research aim, these additional statements are not considered further but interested readers can refer to Jaeger & Giacalone (2021)[3].

Frequency of past consumption. Past consumption frequency was recorded, subsequent to the product characterisations, with the following question: 'How often, on average, have you during the past year consumed [salad/beverage name]?' with the following response categories: 0='never', 1='never in the past 12 months', 2='less than once every 6 months', 3='less than once a month', 4='1-3 times per month', 5='once a week', 6='2-4 times per week', 7='5-6 times per week', and 8='once a day or more'.

Table 1
Emotional, conceptual and situational responses obtained for the salad and beverage stimuli used in the research.

Response	Variables
A. Emotional	Active/alert, Blue/uninspired, Dull/bored, Energetic/excited, Enthusiastic/inspired, Happy/satisfied, Jittery/nervous, Passive/quiet, Relaxed/calm, Secure/at ease, Tense/bothered, Unhappy/dissatisfied
B. Conceptual	Adventurous, Aggressive, Arrogant, Boring, Carefree, Cheap, Classy, Comforting, Confident, Easygoing, Energetic, Feminine, Friendly, Fun, Genuine, Happy, Inspiring, Irritating, Masculine, Modern, Powerful, Pretentious, Sensual, Serious, Simple, Sophisticated, Traditional, Trustworthy, Unique, Youthful
C. Situational – Salads	As a take-out order, As part of an evening meal, For a special occasion, For children, Something that "everyone" will like, To eat at a casual style restaurant, When I want something filling, When I want something healthy, When I'm trying to use up things in the fridge/pantry, When I'm watching my weight
C. Situational – Beverages	As part of breakfast, At a café, For children, In cooking or baking, In the evening, To accompany a sit-down meal, To boost my health, To drink on the go, To quench my thirst, To replace a light meal

[3] Refer to the Table 1, section D in that paper for the list of this items. Jaeger and Giacalone (2021) only refers to Study 2 but items were the same in both studies.

2.4. Implementation

The presentation order of salad/beverage names was sequential and randomized across participants. For all participants, the different parts of the questionnaires were always presented in the order given in Section 2.3. CATA terms and rated statements were always presented in an order randomized for each participant.

Participants completed the survey from a location of their choosing, using a laptop or desktop computer. The survey also covered other topics on food-related consumer behaviour, but these were not relevant to the present research and are not discussed further. The questions pertaining to the salad/beverage stimuli were placed at the start of the survey. The median time to complete the tasks related to this research was 14 min.

2.5. Data analysis

Fitting with the research aim and the EFs, expected liking (Like), emotional responses (Emot), conceptual responses (Conc), and situational responses (Situ) served as explanatory variables/data, while frequency of past consumption was the dependent variable.

The first step was to obtain a characterization of each product for each of the four sets of explanatory data, which was done by building a products × attributes table containing frequencies over products for emotional and conceptual data (which were in a binary format), and means averaged over the participants for situational appropriateness ratings. The same was done for frequency of past consumption to obtain an average for each salad/beverage.

A preliminary ANOVA with participants and products as factors followed by Student t-tests were performed to determine if product means were equal or not for past consumption and liking. Likewise, in order to ascertain key variation in the other sets of response variable, the same ANOVA model was applied to each situational appropriateness statement, whereas for binary responses (emotional and conceptual), Cochran's Q tests were used to identify significant differences among the nine beverage names for each of the 12 emotion word pairs and each of the 30 conceptual terms.

Because the attributes within, respectively, the emotional, conceptual and situational sets of variables were correlated, reduction of dimensionality was the second step. Correspondence Analysis (CA; Greenacre, 2007) was used for emotional and conceptual data, and Principal Component Analysis (PCA; Abdi & Williams, 2010) was used for situational data. For each dataset, the number of components corresponding to 80% of the inertia was retained.

Next, a Spearman correlation matrix (Zar, 2005) was built from the retained components from the emotional, conceptual, and situational data, as well as expected liking and frequency of past consumption. We tested if the correlation was significant or not for each pair of variables.

The retained components from the individual datasets also served as the input data for the prediction of past consumption which used PLS regression (Abdi, 2003). All combinations of explanatory variables were considered, and the models were compared using the Root Mean Square Error (RMSE) obtained by a leave-one-out cross-validation. If within a model, there was a sub-model that included at least one explanatory variable from each of the relevant datasets that performed better, then this model was retained. To find possible better performing sub-models, we used a forward selection procedure with the BIC criterion (Neath & Cavanaugh, 2012).

The predicted R^2 index was also used to evaluate the goodness-of-fit of the different PLS models (Frost, 2019). This index is built on the errors resulting from the leave-one-out instead of the residuals. It avoids the problems of R^2 and adjusted R^2 linked to overfitting and is compatible with PLS regression (Price et al., 2009). This index is equal to 0 if the prediction is equal to the prediction which consists in using the mean of response variable, and equal to 1 if the predictions are perfect.

All analyses were performed in R software v. 3.6.0 (R Core team, 2019).

3. Results

3.1. Preliminary analyses

Table 2 provides means and *post hoc* comparisons pertaining to frequency of past consumption and liking. The ANOVA on liking and past consumption with participants and products as factors showed that both effects were highly significant ($p < 10^{-16}$). The range of frequency of past consumption was different across the two studies. In Study 1 (Salads), none of the products was very frequently consumed; the product with the highest mean past consumption frequency was *Mixed green salad* (mean of 3.65, in between 'less than once a month' and '1–3 per month'). By contrast, Study 2 (Beverages) spanned a much larger range in terms of consumption frequency, and also featured two products (*Still water* and *Cow's milk*) consumed weekly or more, on average (Table 2). Differences in liking across products were similar in both studies (Study 1 range: 4.1–5.8; Study 2 range: 3.6–5.9).

The univariate analyses performed on the other sets of variables (ANOVA for the situational appropriateness ratings, Cochran's Q for the Emotional and Conceptual variables) also confirmed that successful product differentiation was achieved for all variables in all datasets (Part 3 of Supplementary material), with the exception of three conceptual attributes ("Sensual", "Serious" and "Youthful") which did not discriminate between the salads in Study 1.

3.2. Dimensionality reduction and relationships between explanatory variables

The first step of the analysis consisted in extracting dimensions from the individual sets of explanatory variables meeting the retention criteria (≥80% of original inertia). On this basis, the number of dimensions retained in each dataset was identical in both studies: 2 dimensions for emotional variables, 3 dimensions for conceptual variables, 2 dimensions for situational appropriateness (Part 3 of Supplementary Material has in-depth results for individual datasets, including multivariate plots, eigenvalues and variance explained by component).

Table 3 shows the correlations between these model dimensions as well as with liking, linked to EF1. Starting with the former, the correlation between liking and emotions was different in the two studies (Table 3). In Study 1 (Salads), liking was highly correlated with the first dimension of the emotion data (Emot1), which clearly related to valence (e.g., it opposed emotion terms such as "happy-satisfied" to "unhappy-dissatisfied"). By contrast, the second dimension (Emot2) mostly captured arousal ("Calm, relaxed" vs "Enthusiastic, inspired") and accordingly was uncorrelated with liking. In Study 2 (Beverages), valence and arousal terms were associated with both the first and the second emotion dimensions and accordingly, liking was significantly, but moderately, correlated with both. Finally, liking in both studies was correlated with the first dimensions of the conceptual (Conc1, $|r| \geq 0.67$) and situational data (Situ 1, $r \geq 0.88$). Conc1 appeared broadly related to valence (e.g., in both studies, it opposed negative terms – such as "aggressive", "pretentious", "arrogant", to positive ones – such as "traditional", "trustworthy", "comforting"). In Study 1, Conc2 opposed terms such as "cheap" and "boring" to "classy" and "sophisticated", whereas Conc3 separated products characterized as "masculine" and "aggressive" from "feminine" ones; this was the same in Study 2, although the weighing of specific variables differed. For the situational data, all the original situational statements were positively loaded on Situ1, indicating that consumers who found a product appropriate for one situation tended also to find it appropriate in most other situations. In other words, Situ1 ranked product by less to more appropriate, explaining why this dimension was highly correlated with liking in both studies. The second dimension (Situ2) in Study 1 (Salads) was related to two situations relating to health, rather than valence ("When I am watching my weight" and "When I want to eat something healthy"), and accordingly, this was uncorrelated to liking (Table 3). In Study 2 (Beverages), Situ2 was associated to beverages appropriate "At a cafè" and "To drink on the go", and again was uncorrelated to liking (Table 3). For additional in-depth results on specific datasets we refer the reader to Part 3 and Part 4 of Supplementary Material for Study 1 and Study 2, respectively.

Table 2
Product-specific results showing means for frequency of past consumption and liking. Products are ranked by frequency of past consumption. Within columns, means that do not share superscript letters are significantly different (Student t-tests).

Product name	Avg. Freq. Past Consumption*	Avg. Liking **
Study 1 (Salads)		
Mixed greens salad	3.6 [a]	5.6 [d]
Caesar salad	3.0 [b]	5.8 [b]
Pasta salad	2.8 [c]	5.5 [d]
Caesar salad with chicken	2.7 [c]	5.8 [b]
Coleslaw	2.6 [c]	5.0 [a]
Cobb salad	1.9 [d]	5.1 [a]
Mixed greens salad with tuna	1.7 [d]	4.7 [c]
Pasta salad with beef	1.4 [e]	4.7 [c]
Coleslaw (vegan mayonnaise)	1.2 [e]	4.1 [e]
Study 2 (Beverages)		
Still water	5.9 [a]	5.9 [e]
Cow's milk	4.9 [b]	5.6 [d]
Fruit smoothie	3.0 [c]	5.6 [d]
Iced coffee	3.0 [c]	4.8 [f]
Energy drink	2.1 [d]	3.7 [bc]
Iced coffee with almond milk	1.8 [d]	4.4 [a]
Oat milk	1.4 [e]	3.9 [c]
Fruit smoothie with soy milk	1.4 [e]	4.4 [a]
Kombucha	1.4 [e]	3.6 [b]

Notes. *) Frequency of past consumption was measured with the following response categories: 0='never', 1='never in the past 12 months', 2='less than once every 6 months', 3='less than once a month', 4='1-3 times per month', 5='once a week', 6='2-4 times per week', 7='5-6 times per week', and 8='once a day or more'. **) 9-pt hedonic scale.

3.3. Prediction of past consumption frequency from liking, emotional, conceptual and situational appropriateness data

Fig. 2 shows correlations between frequency of past consumption with liking and with retained dimension for the 'beyond liking' beyond liking dataset. As shown in Fig. 2, past consumption was positively correlated with liking (in both studies: Spearman's $r \geq 0.83$). Additionally, in both studies one dimension of emotional, conceptual, and situational data was highly correlated with past consumption (Spearman's $|r| \geq 0.82$ in Study 1 and $|r| \geq 0.62$ in Study 2). However, patterns of correlations were different across studies: in Study 1 (Salads), it was the first dimension from each 'beyond liking' dataset that highly correlated with past consumption (Fig. 2A); by contrast, in Study 2 (Beverages) the second dimension of the emotion data (Emot2) was more correlated with past consumption than the first dimension in the same dataset, and both for the conceptual data, both the first and the second dimensions were highly correlated with past consumption (Fig. 2B).

The second step in the analysis consisted of prediction of past consumption from the model dimensions extracted from the individual datasets and contributed to EF2 and EF3. Results of these analysis are given in Table 4, which compares all model combinations in terms of prediction error (RMSE) and predicted R^2, and in Fig. 3, which provides prediction errors for individual products.

Inspection of Table 4 and Fig. 3 revealed differences between the two studies. In Study 1 (Salads), past consumption was predicted better by liking alone with 60% of the variance explained, whereas in Study 2 (Beverages) this was lower and more importantly, the prediction error for the same model was more than twice as large (cf. first row in

Table 3
Spearman correlation matrices between expected liking and retained model dimensions for emotional, conceptual, and situational data, calculated across the nine stimuli in each study. *: $p < 0.1$. **: $p < 0.05$.

2A) Study 1 (Salads)

	Emot1	Emot2	Conc1	Conc2	Conc3	Situ1	Situ2	Liking
Emot1	1	−0.05	0.62*	−0.50	−0.07	−0.93**	0.23	−0.98**
Emot2		1	0.62*	0.73**	0.18	−0.07	0.18	0.02
Conc1			1	0.13	0.25	−0.72**	0.05	−0.67*
Conc2				1	−0.17	0.32	0.43	0.47
Conc3					1	0.10	−0.57	0.08
Situ1						1	−0.05	0.97**
Situ2							1	0.10
Liking								1

2B) Study 2 (Beverages)

	Emot1	Emot2	Conc1	Conc2	Conc3	Situ1	Situ2	Liking
Emot1	1	0.37	0.80**	0.00	−0.10	−0.93**	0.17	−0.73**
Emot2		1	0.48	−0.73**	0.52	−0.42	−0.15	−0.65*
Conc1			1	−0.23	0.07	−0.93**	−0.13	−0.92**
Conc2				1	−0.20	0.10	0.13	0.37
Conc3					1	0.00	−0.77**	−0.38
Situ1						1	0.00	0.88**
Situ2							1	0.38
Liking								1

Notes. Emot = Emotional, Conc = Conceptual, Situ = Situational. The numerical suffixes signify dimension (e.g., Situ2 = second dimension in situational appropriateness data).

Table 4).

By construction, both prediction error measures and goodness-of-fit statistics gave identical indications with respect to the prediction ability of the different PLS models. In Study 1 (Salads), the best fitting model included liking and emotional data (Table 4). This model yielded the most accurate prediction (lowest RMSE) and explained 93% of the variation in past consumption of salads. In line with EF2, the improvement from adding emotions to liking was very notable when looking at the change in RMSE for individual products (Fig. 3A) (note that RMSE is expressed in the same unit as the response variable, i.e., the scale measuring the frequency of past consumption). Fig. 3A shows that predicted values from liking alone were clearly inaccurate for several of the products (*Cobb salad, Caesar salad with chicken, Coleslaw, Mixed green salad*, *Pasta salad with beef*), whereas in the best fitting model all products but two (*Cobb salad* and *Caesar salad with chicken*) were predicted with much greater accuracy (RMSE $\leq$ 0.24). Since Emot1 (valence) was highly correlated with liking (Table 3), the improvement in predictive ability could probably be attributed to Emot2 (arousal); this was supported by the large loading of Emot2 on the second PLS component whereas Liking and Emot1 contributed very little to this component (Part 3 of Supplementary Material). Addition of the other two datasets (conceptualizations and situational) did not improve prediction relative to the liking and emotion model, and decreased prediction accuracy overall, except for the two products not well explained by the best model (*Caesar salad with chicken* and *Coleslaw*, data not shown).

Study 2 (Beverages) showed quite different results. In this dataset, the prediction of past consumption from liking alone was lower than in Study 1, and in contrast to Study 1, emotions did not contribute to explaining variation in past consumption (Table 4), likely because both emotion dimensions were significantly correlated with liking (Table 3). Instead, the addition of situational and conceptual dimensions improved both fit and accuracy for the model. The addition of conceptualizations especially resulted in a large improvement. Accordingly, the best model was found to be the one with liking, conceptual and situational variables, which explained 93% of the variance in past consumption (Table 4) and majorly improved the prediction accuracy of all products (Fig. 3B) compared with the model with liking alone, with the exceptions of two products (*Kombucha* and *Iced coffee*). Overall, results from both studies, therefore, indicate an improvement in prediction of behavioural response in line with expectations (EF2), although the best combination of predictors was different between Study 1 and Study 2.

With respect to EF3, Table 3 results already showed liking to be highly correlated with many of the other explanatory variables, suggesting that at least one dimension from the "beyond liking" datasets in both studies carried hedonic information as well. To directly evaluate EF3, we also calculated the RMSE and goodness-of-fit for each best PLS models *without the liking.* In Study 1 (Salads), the model without liking yielded a RMSE = 0.21 and Predicted $R^2 = 0.93$. In Study 2 (Beverages), values were RMSE = 0.44 and Predicted $R^2 = 0.92$. In both studies, these values were practically identical to those obtained when liking was included (Table 4), suggesting that the best "beyond liking" models perform just as well without a separate liking variable, which supports EF3.

4. Discussion

4.1. Empirical support for the expected findings and practical implications

In support of EF1, liking was highly correlated with past consumption in both studies, and the same was found for at least one of the dimensions in the other datasets (Fig. 2). The finding that liking correlates with consumption is obviously not surprising. Consumers eat what they like, and – since food preferences are mainly learned through experience (Köster, 2009) – they also like what they eat. More interesting is the finding that emotional, conceptual, and situational responses were significantly correlated with past consumption, as this has not been previously reported and provides a first line of evidence linking these "beyond liking" product measures to actual consumer behaviour. This also fits with experimental evidence on other aspects of food-related behaviour, specifically food choice, for which previous studies uncovered a link to emotions (Gutjar et al., 2015a, Gutjar et al., 2015b) and situational appropriateness data (Giacalone & Jaeger, 2019b), and showed an improvement in predictive value relative to liking ratings.

In accordance with EF2, both studies showed that the inclusion of "beyond liking" measures substantially improved prediction of past behaviour (with respect to both model fit and prediction accuracy) compared with prediction based on liking only (Table 4). This empirically supported calls for the purposeful combination of different response types using "global" or multi-response approaches to better capture consumer experiences with foods and beverages (Cardello et al.,

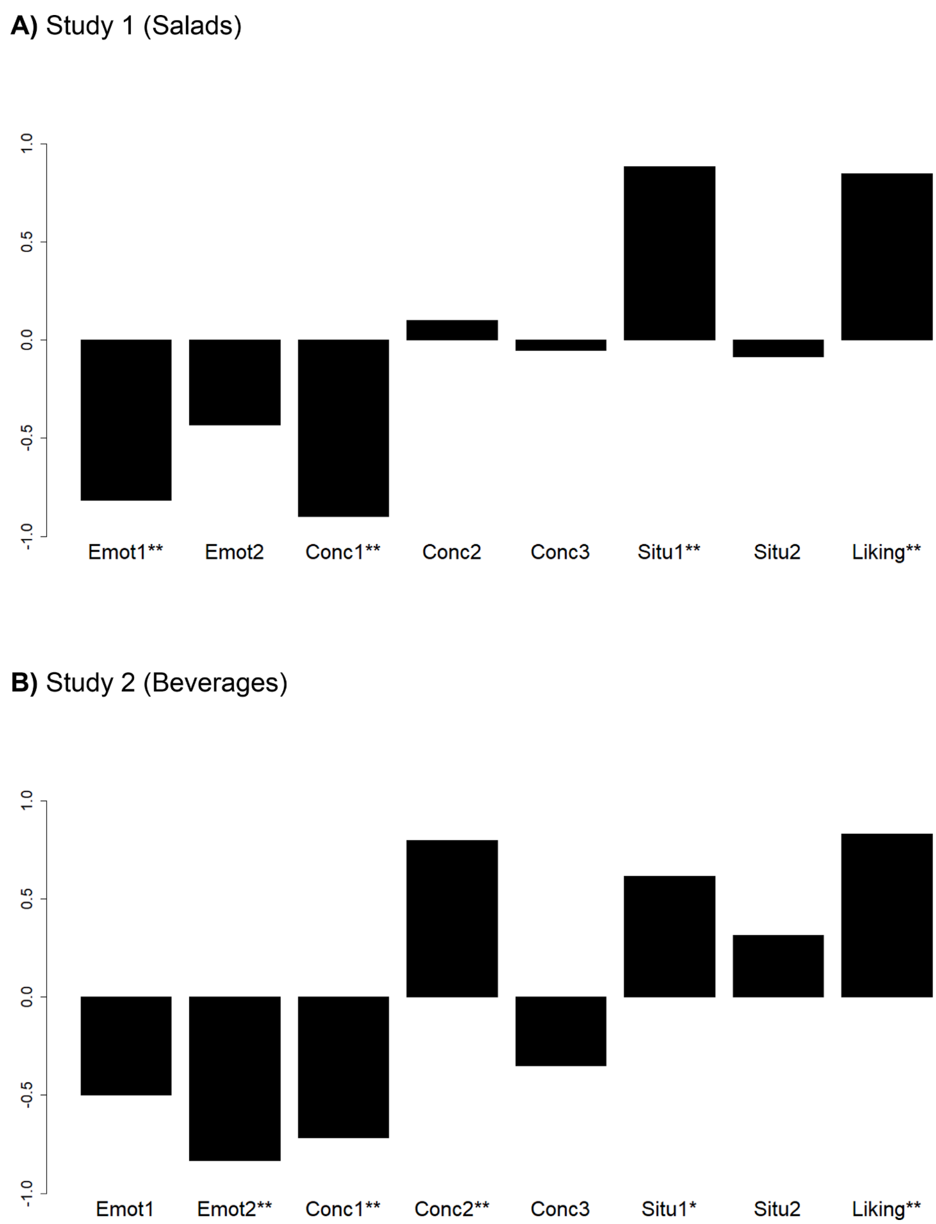

Fig. 2. Bar plots showing correlations (Spearman) between frequency of past consumption with each retained dimensions for emotional (Emot), conceptual (Conc), situational data (Situ), and expected liking, calculated across the nine stimuli in each study. *: $p < 0.1$. **: $p < 0.05$.

Table 4
Prediction error (RMSE) and goodness-of-fit (Predicted R^2) for PLS models to predict frequency of past consumption based on different datasets. Shown for Study 1 (Salads) and Study 2 (Beverages). The best PLS model in each study is indicated by an asterisk (*).

Datasets in model	Study 1 (Salads)		Study 2 (Beverages)	
	RMSE	Pred. R^2	RMSE	Pred. R^2
Liking	0.49	0.60	1.10	0.49
Liking + Emotional	0.20*	0.93*	1.14	0.46
Liking + Situational	0.51	0.59	1.08	0.51
Liking + Conceptual	0.26	0.89	0.59	0.85
Liking + Emotional + Situational	0.22	0.91	1.25	0.35
Liking + Conceptual + Situational	0.30	0.85	0.41*	0.93*
Liking + Emotional + Conceptual	0.20	0.93	0.59	0.86
Liking + Emotional + Conceptual + Situational	0.22	0.92	0.49	0.90

2016, Jaeger et al., 2017; Jaeger et al., 2020a; Spinelli et al., 2019) and confirmed that that liking in and of itself is insufficient as a predictor of consumption, in line with past findings (Cardello et al., 2000; Rosas-Nexticapa, Angulo, & O'Mahony, 2005).

While prediction of past consumption was improved by combining liking and "beyond liking" measures in both studies (EF2), the "beyond liking" datasets that contributed to this improvement differed, hereby pointing to study-specific influences. In Study 1 (Salads), the optimal combination of predictors included liking and emotional responses, and it was mainly Emot2 that improved prediction, whereas Emot1 captured hedonic differences. In other words, a combination of valence and arousal optimally explained the variation in past behaviour for the salads stimuli. In Study 2 (Beverages) liking alone predicted much less of the variance in past consumption than it did in Study 1 and the best model combined liking with conceptual and situational data, whereas emotional data did not improve prediction of past consumption in Study 2 (Table 4). The main reason underpinning this difference may be that Study 1 had a more homogeneous set of products, as it focused on just

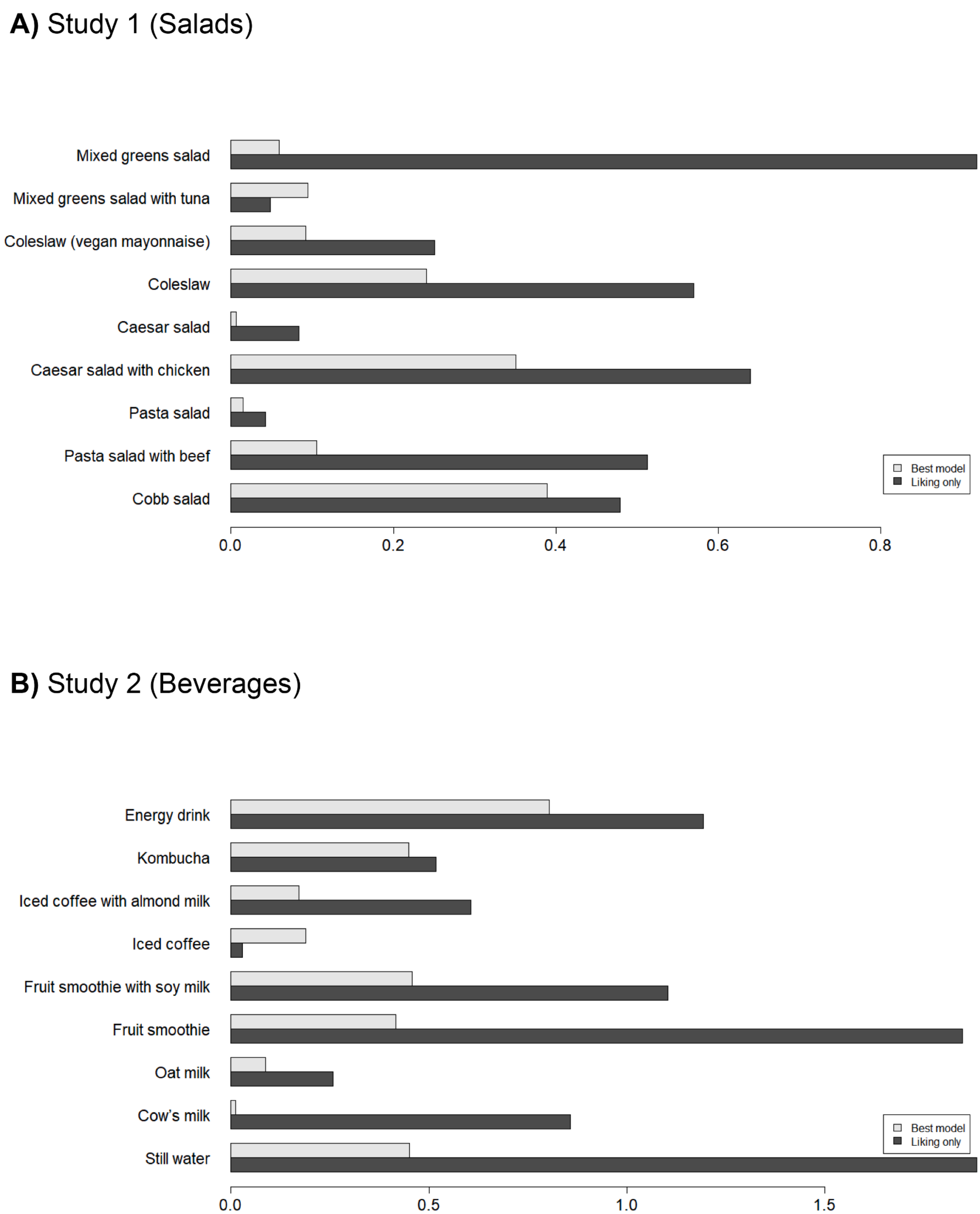

Fig. 3. Bar plots showing prediction error (RMSE) for past consumption frequency of individual products. Values for the best PLS model (i.e., lowest RMSE) are shown next to predictions based on expected liking only. RMSE is expressed in the same unit as the frequency of past consumption, which was measured with the following response categories: 0='never', 1='never in the past 12 months', 2='less than once every 6 months', 3='less than once a month', 4='1-3 times per month', 5='once a week', 6='2-4 times per week', 7='5-6 times per week', and 8='once a day or more'.

one product category (salads), whereas Study 2 (beverages) included very diverse products that can fit different situations.

Taken together, this suggests that the optimal combination of "beyond liking" measures to predict consumption is going to be study-specific. In general, however, both studies suggested that adequate prediction of product consumption will require both hedonic and additional measures. The general recommendation for practitioners is to conduct pilot testing to ascertain the relevance of different measures for the focal product set. Relatedly, our results suggest that it makes sense to be open to different "beyond liking" measures having the potential to substantially improve prediction of behaviour (beyond a liking-only model) rather than having a narrow focus on only one area, as has been a past tendency. Practitioners should, instead, embrace the notion that study-specific influences are likely to occur and beware of attempting to determine *a priori* the relative value of each "beyond liking" type of data.

A pragmatic recommendation, based on this study and the general authors' experiences with "beyond liking" measures, would be to try and reduce the items in each of these additional measures in order to allow all to be collected but also to maximize their informational value. For example, it is important that the emotional questions cover the arousal dimension (which is not always the case). For situational appropriateness, it seems important to think about consumption contexts that will differentiate between the focal products, rather than just be applicable to the product category as a whole. As argued elsewhere (Giacalone & Jaeger, 2021), adopting an approach to term selection/development akin to what commonly done to develop attributes for sensory descriptive analysis is likely to maximize sample discrimination, which is ultimately where their predictive contribution comes from. Relatedly, the approach to situational appropriateness used in this research was of nomothethic character, that is, one set of usage situations is evaluated by all consumers, with the implicit assumption that all situations are relevant to all consumers, which is generally not the case. While providing a comprehensive list of situations at least some of them are, it is likely that the contribution of appropriateness data to explaining consumption could be enhanced if consumers were free to develop their own set of usage situations, which could be done using ideographic approaches such as the Repertory Grid method (Giacalone & Jaeger, 2019a,b). The same point could be extended to conceptualizations and emotions as well, as words relevant for individual consumers could be missing.

Let us now consider the last proposition considered in this research (EF3), which speculated that a separate liking question would not be necessary if emotional, conceptual, and situational data are available. In general, both studies evidenced clear and strong correlation between liking and "beyond liking" measures. At least the first dimension of each data type produced a very similar product ranking as one would obtain from hedonic responses, so in terms of informational value "beyond liking" responses, despite the moniker, actually capture liking as well. Crucially, in both studies we found that the PLS models including the optimal combination of "beyond liking" measures (Table 4) predicted consumption just as well even when liking was excluded. Thus, EF3 was also overall supported by the data.

In principle, this suggests that one can dispense with asking a separate liking question with no loss of informational value, although in practise this will need to be weighed against other considerations. Liking is a single question, which makes it a parsimonious way to collect hedonic responses, whereas capturing valence with other type of measures requires evaluation of several variables and a qualitative investigation of the findings. Besides efficiency, the single-question formal also has several practical advantages for data analyses (e.g., clustering, preference mapping) compared with multi-response measures. Relatedly, while in this research one dimension of additional measures could usually be interpreted as valence, this may not always be the case. For example, multivariate decomposition of emotional data indicates that both valence and arousal may be simultaneously represented in the same model dimension (Jaeger et al., 2020b), making interpretation less straightforward. Finally, especially in industry situations, there may be non-scientific yet good arguments for collecting hedonic data separately, such as benchmarking new test results with historical data, and ease of communication for topline findings.

4.2. Limitations and suggestions for future research

This paper has begun to relate "beyond liking" measures to previous consumption. Being one of the few papers to do so and given the general paucity of literature relating sensory and consumer data to actual behaviour, future studies confirming and expanding the findings are encouraged.

There are two main limitations which constitute avenues for future research. The first concerns the type of stimuli, which in both studies were product names rather than actual foods and beverages and led to expected liking rather than actual liking being the hedonic response. Although there is a long history of employing product names in consumer liking tests (e.g., Schutz & Cardello, 2001), this type of stimuli may limit the external validity of the findings (Schutz, 1988); for instance, because consumers may form different mental images in response to the same verbal stimulus. Therefore, a logical next step would consist in replicating this research using physical (tasted) product samples in either a central location or home-use test. Restricting the stimuli range to closer substitutes would also be relevant: this would correspond to what could be done by a company in their internal sensory and consumer programs, and thus increase the practical relevance of this research. Relatedly, the use of specific branded products might would lend itself to the studying the performance of "beyond liking" measures with respect to frequency of purchase, rather than frequency of consumption as in the present research. While reasonable to assume that the two will be highly correlated (in independently living adults), they are not equivalent, and from a company's perspective frequency of purchase might be the more immediately relevant measure.

The second main limitation relates to the level of analysis. This research has considered aggregated level analyses and prediction of frequency of consumption of the "average consumer". In future studies, it would be interesting to attempt analyses on individual-level data and consider segmentation in the behavioural responses. This could help identify differences in the relative importance of different predictors for individual consumers. For example, people are known to differ in the way they verbalize and distinguish emotional states, the so-called "emotional granularity" (Spinelli, 2017). One could expect that the predictive ability of emotional and conceptual data would be higher for consumers who are able to make fine-grained, nuanced distinctions between emotional states. In turn, the behaviour of consumers with lower emotional granularity may be best predicted by other measures or by hedonics alone. Similarly, consumers differ in the degree to which they discriminate products based on situational appropriateness (Jaeger et al., 2019, 2021). Therefore, situational appropriateness data may possibly be more relevant to predict consumption in those individuals reflecting a differential in conformity to common norms about what is appropriate to eat and drink at different occasions, or who are simply are more oriented by functional considerations in their choices. With the present data, we did not find that the level of analysis affected the conclusions, as undertaking individual-level analyses (Part 5 in Supplementary Material) lead to similar conclusions as to which combination of variables best predicted consumption frequency. There was, however, a small discrepancy with respect to Study 1 (Salads), in which the most predictive model using individual-level ("unfolded" data) analyses included liking, emotional and *situational* predictors, whereas at the aggregated it only included the first two predictors (cf. Table 3 and Part 5 of Supplementary Materials). A possible reason for this might relate to the just outlined differential in conformity to norms about what is appropriate to eat and drink at different occasions. Possibly, in this particular dataset the consumers regarding a wide variety of products as appropriate regardless of situations was larger than those who more strictly observe cultural norms. This might explain which differences in appropriateness might be downplayed when analyzing data at the aggregated level, and explain why at the individual level there would still be a gain in prediction.

To reiterate, the aggregate level of analyses was deemed appropriate in relation to the study overall objective which was not to predict consumption *at the individual level* but rather to provide an initial benchmark of the ability of different measures to predict behaviour. However, understanding these individual differences should be a useful continuation of this line of work.

5. Conclusions

Situated within the context of increased interest in perceptual responses "beyond liking", the present study sought to evaluate the ability of emotional, conceptual, and situational appropriateness measures to predict a behaviourally relevant measure of product performance – past consumption.

Three propositions (expected findings) were explicitly considered: i) that liking, emotional, conceptual, and situational responses would be significantly correlated with behavioural responses (EF1); ii) that inclusion of "beyond liking" measures would improve prediction over and above that based on hedonic responses only (EF2); and iii) that a separate liking response may not be necessary if such responses are available (EF3). To evaluate them, we presented findings from two consumer studies pertaining respectively to salads (Study 1) and non-alcoholic beverages (Study 2), in which the predictive ability of each set of measures was benchmarked against that of expected liking to identify the optimal (most predictive of consumption) combination of product-related measures.

Supporting both EF1 and EF2, the two studies provided converging evidence that all included measures (liking, emotional, conceptual, and situational responses) were significantly correlated with frequency of past consumption, and importantly, that inclusion of "beyond liking" measures improved behavioural prediction over and above that of models based on hedonic responses only. While a linkage between liking and consumption was expected, this research provides the first line of evidence linking measures of emotional, conceptual, and situational responses to actual consumer behaviour. Furthermore, the findings support the notion that liking in and of itself is insufficient as a predictor of consumption, and they support calls for the purposeful combination of different response types using "global" or multi-response approaches. Additionally, both studies also evidenced clear and strong correlations between liking and "beyond liking" measures and, accordingly, the latter predicted consumption equally well when liking (as a separate variable) was not used as a separate predictor in the model. This supported the last proposition considered in this research (EF3) that a separate liking question may not be necessary if emotional, conceptual, and situational data are available.

However, differences between the two studies (pertaining to the relative importance of liking and the best combination of predictors) were uncovered, suggesting the optimal combination of "beyond liking" measures in practical applications should be a consequential topic for future research.

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CRediT authorship contribution statement

Davide Giacalone: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Fabien Llobell:** Formal analysis, Writing – original draft, Writing – review & editing. **Sara R. Jaeger:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodqual.2021.104459.

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