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Short Communication

Using correlation matrices to standardise sweet liking status classification

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ABSTRACT

Distinct hedonic patterns of sweet taste liking have been widely recognised for more than half a century. Despite there being a growing consensus on the role of Sweet Liking Status (SLS) in food choice behaviour, current classification methods for this phenotype generally lack consistency. Using a large dataset (n = 865), the present study applied Agglomerative Hierarchical Clustering (AHC) followed by correlation matrices as a validated and robust method for SLS classification by using five sucrose solutions (3, 6, 12, 24 and 36 %). As demonstrated in the present study, AHC alone was not a sufficient method to generate reliable SLS clusters. Following a validated correlation matrix approach, three distinct consumer clusters were identified: High Sweet Likers (HSL), Medium Sweet Likers (MSL) and Low Sweet Likers (LSL). Robust mean liking scores were generated for each of the three clusters across five different concentrations of sucrose. The results suggested that in order to enable more efficient and comprehensive SLS classification, a correlation-based approach for SLS classification using the validated liking means provided in the current study should be adopted in future research. In addition, a rapid three-solution method (3 %, 12 % and 36 %) was also explored as a simplified and more efficient way of classifying participants for SLS. The rapid three-solution method accurately classified the majority of HSL, MSL and LSL within the dataset. The data showed a good level of agreement between the rapid three-solution method and validated five-solution method, therefore suggesting that a rapid three-solution method can be considered when exploring the two hedonic extremes (HSL and LSL) when additional noise in the data can be tolerated.

1. Introduction:

Dietary habit is a determinant of long-term health outcomes, particularly in regard to the prevention and management of obesity, diabetes and cardiovascular disease. Excessive sugar consumption has been associated with an increased risk of these diseases (Lean & Te Morenga, 2016; Malik et al., 2010). Humans are born with an innate preference for sweet taste, which draws from an evolutionary perspective as sweet food signals energy (Chaudhari & Roper, 2010). Infants have been shown to display positive facial expressions in response to sweet stimuli (Forestell & Mennella, 2017). In today's market, differences in consumer preferences towards sweet foods are clearly highlighted by the wide variety of food and beverage products available.

Sweet Liking Status (SLS) has been researched extensively since the 1970s. Pangborn (1970) first reported this taste phenotype and identified that the preferred sweetness level differed across individuals, classifying subjects as sweet likers and sweet dislikers. When different concentrations of sugar solutions were presented, sweet likers typically preferred the higher concentrations whereas sweet dislikers typically preferred the lower concentrations. To date, several classification methods have been reported to identify the distinct hedonic responses to sweet taste. The first approach looked at the pattern of hedonic response curves by visual identification (Pangborn, 1970), the second approach used a cut-off point approach (Yeomans et al., 2009), and the third approach used a paired preference approach to identify the optimal/rejection point (Mennella, Finkbeiner, Lipchock, Hwang, & Reed, 2014). The fourth approach adopted statistical analysis using Agglomerative Hierarchical Clustering (AHC), which was used more widely by recent researchers (Kim, Prescott, & Kim, 2017; Kim, Prescott, & Kim, 2014; Methven, Xiao, Cai, & Prescott, 2016). However, inconsistent cluster groups have been identified. For example, Methven et al. (2016) identified two cluster groups – sweet likers and sweet dislikers. In contrast, Kim et al. (2014) identified three distinct consumer clusters based on liking for sucrose solutions and sweetened beverages: Cluster 1 showed an increased liking pattern for increasing sweetness for both the solutions and beverages, Cluster 2 was defined by an increase in liking for increasing sweetness in the beverages but not in the sucrose solutions, while Cluster 3 followed an inverted U-curve in both matrices. A more

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recent study by Kim et al. (2017) identified five clusters initially, then further grouped them into sweet likers and sweet dislikers and the unclassified cluster that showed no clear preference for either strong or weak sucrose solutions. Yang et al. (2019) suggested a modified approach using AHC followed by correlation matrices and identified four consumer clusters: High Sweet Likers (HSL, equivalent to sweet likers), Medium Sweet Likers (MSL, inverted U-shaped with highest preference for medium intensity sweetness), Low Sweet Likers (LSL, equivalent to sweet dislikers) and Unclassified (UN, no clear pattern). Despite the use of similar statistical approaches, these studies highlight that the number and liking patterns of SLS clusters are inconsistent. Moreover, the lack of a standardised classification method presents challenges when comparing results across different sweet liking studies, as highlighted recently by both Yang et al., and Iatridi et al., 2019. Therefore, this study investigated a combined dataset from seven studies exploring SLS ($n = 865$), that used the same five sucrose solution approach in order to develop a universal validated clustering method. In addition, a rapid classification technique using hedonic data from three sucrose solutions was explored to examine the feasibility of a simplified and robust SLS clustering method.

2. Materials and methods

2.1. Participants

Eight hundreds sixty-five participants were recruited from seven different studies conducted at the Sensory Science Centre, University of Nottingham from 2017 to 2022. The data from the studies was combined to create a large dataset. All procedures were reviewed and approved by the Faculty of Medicine and Health Sciences or the School of Biosciences Research Ethics Committees at the University of Nottingham.

2.2. Sweet liking Status screening

To ensure correct use of the general Labelled Magnitude Scale (gLMS) (Bartoshuk et al., 2002), all participants completed a familiarisation exercise, as described previously by Low et al. (2017). The familiarisation involved asking participants to write down their own strongest sensation of any kind that either they have experienced previously or the strongest sensation they could imagine experiencing, which subsequently represented the top of the scale. Participants were then asked to rate the intensities of five remembered or imagined sensations (e.g. 'loudness of a whisper', 'bitterness of black coffee', 'coldness experienced sucking on an ice-cube', 'sweetness of candyfloss', and 'strongest oral pain ever experienced'), relative to their own strongest sensations (Bartoshuk et al., 2002).

After the familiarisation exercise, participants were presented with five sucrose solutions (3 %, 6 %, 12 %, 24 % and 36 % w/v) monadically. The range of concentrations was selected based on commonly used concentrations for measuring sucrose preference in previous literature (Kim et al., 2014; Mennella et al., 2014). Sucrose was dissolved in Evian water (Evian, Danone, France) and placed on the roller bed for 15 min to ensure it was fully dissolved. Samples were prepared either the day before or on the day of testing and stored refrigerated at 4 °C until 1 h before use (serving temperature 20 ± 2 °C). Each participant was instructed to drink the sucrose samples provided (10 ml) and rate how much they like the taste on a Labelled Magnitude Scale (LAM) (Schutz & Cardello, 2001) and the intensity of sweetness on the gLMS (Bartoshuk et al., 2002). The presentation for the five sucrose solutions was randomised, without the weakest and strongest samples following each other to minimise contrast the effect (Ferris, Kempton, & Muir, 2003). Two-minute breaks were given in between samples and participants were asked to cleanse their palate with water (Evian, Danone, France) and crackers (Carr's Table Water Biscuits, Pladis, UK).

2.3. Data analysis

In order to group consumers into initial clusters based on the liking score patterns, Agglomerative Hierarchical Clustering (AHC) using Ward's method and dissimilarity was performed on the liking data of the five sucrose solutions for all seven individual studies and the combined dataset. Then, a correlation matrix using Pearson's correlation was performed to evaluate the relationship between each consumers' liking scores and cluster means across the five sucrose concentrations, as previously described by Yang et al. (2019). Cluster means for the correlation matrix were obtained from the AHC. Lastly, to determine if the clusters identified by AHC were valid, the correlation coefficients for each consumers' individual liking scores with the cluster means were evaluated. Briefly, a consumer was considered a valid member of a cluster if the correlation coefficient was above 0.6. Consumers with correlation coefficients below 0.6 for the cluster assigned during AHC were reclassified. More details and examples are provided in Section 3.1.

Once the validated SLS clusters had been developed, a rapid three-solution method was explored by conducting correlation matrix between each consumer's liking and cluster means for the liking scores of three different sucrose concentrations (3 %, 12 % and 36 %). Two-way Analysis of Variance (ANOVA) (concentration, SLS), with interactions, was conducted on liking and perceived sweetness intensity. Where significant effects were observed, further Tukey's Honest Significant Difference (HSD) was applied. Concordance was measured between the validated five- solution method, and both initial AHC and rapid three-solution method using Cohen's Kappa. Agreement between the classification schemes was considered poor ($\kappa < 0.200$), fair ($\kappa = 0.201$–0.400), moderate ($\kappa = 0.401$–0.601), good ($\kappa = 0.601$-0.800) or excellent ($\kappa > 0.800$) (Kwiecien, Kopp-Schneider, & Blettner, 2011). All statistical analysis were performed using XLSTAT version 2022.1.2 (Addinsoft, Paris, France) at an α-risk of 0.05.

3. Results

3.1. SLS classification validation with five solutions

The primary objective of this study was to develop a standardised classification method for Sweet Liking Status. As shown in Fig. 1a, the standard AHC method initially assigned 308 participants to Cluster 1 (correlation coefficient between each participant and Cluster 1 mean score ranged from −0.94 to 0.99). Cluster 1 showed increasing liking with increasing sucrose concentration and were therefore categorised as HSL. 276 participants were assigned to Cluster 2 (correlation coefficient between each participant and Cluster 2 mean score ranged from −0.29 to 0.99) and were named LSL, since their liking decreased with increasing sweetness. Lastly, 281 participants were assigned to Cluster 3 (correlation coefficient between each participant and Cluster 3 mean score ranged from −0.51 to 0.97) and were categorised as MSL.

The negative correlation observed in each cluster suggested the potential misclassification of some participants. Therefore, following Yang et al., (2019)'s approach, reclassification was implemented for those consumers whose correlation coefficient with the cluster mean was below 0.6. Fig. 2 shows some individual reclassification examples. The participant in Fig. 2a was initially assigned to Cluster 1 (HSL) and had the correlation coefficient of 0.45 with the cluster mean. The same participant however, showed a much higher correlation coefficient with Cluster 2 (LSL) ($r = 0.85$) and was therefore reclassified as LSL. Following the same approach, the participant in Fig. 2b was initially assigned to Cluster 1 (HSL, $r = 0.1$), and was reclassified as MSL, as $r = 0.91$ with Cluster 3 (MSL) was observed. The subject in Fig. 2c was initially classified as MSL, however, due to having poor correlation with all three cluster means ($r < 0.6$), this participant was then assigned to the Unclassified (UN) group. The participant in Fig. 2d was initially classified as MSL ($r = 0.57$), and was reclassified as LSL ($r = 0.89$).

Using this approach, 299 subjects were reclassified, representing 34

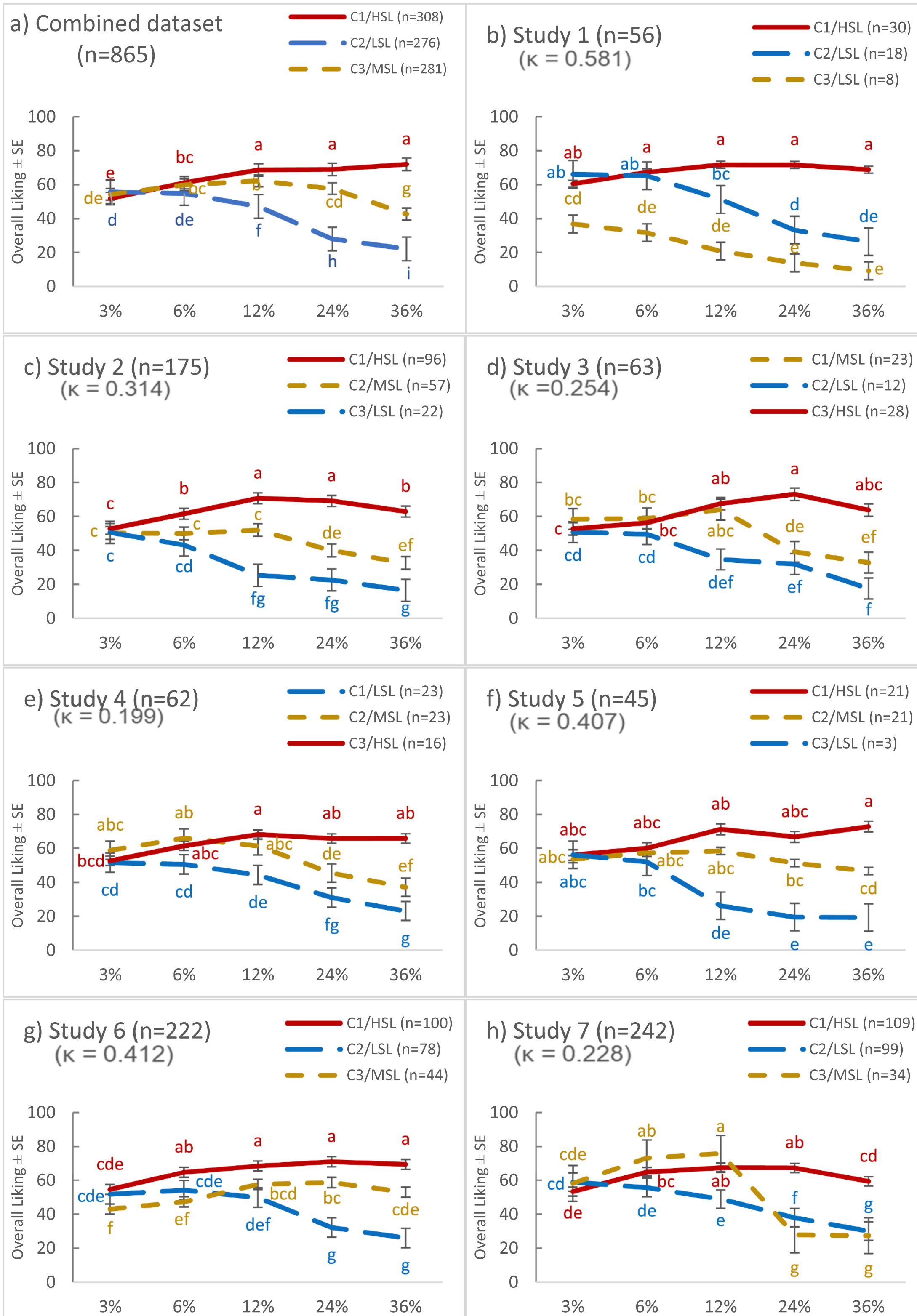

Fig. 1. Overall liking for 3 %, 6 %, 12 %, 24 % and 36 % sucrose solutions among AHC clusters for combined dataset (a) and 7 studies (b-h) conducted at the University of Nottingham from 2017 to 2021. Different letters indicate significant difference ($p \leq 0.05$). Data from study c (Yang et al., 2019) has been previously used in publications to determine SLS. All other data is currently unpublished. By combining the data across seven studies, a large dataset was obtained allowing for new research questions to be investigated.

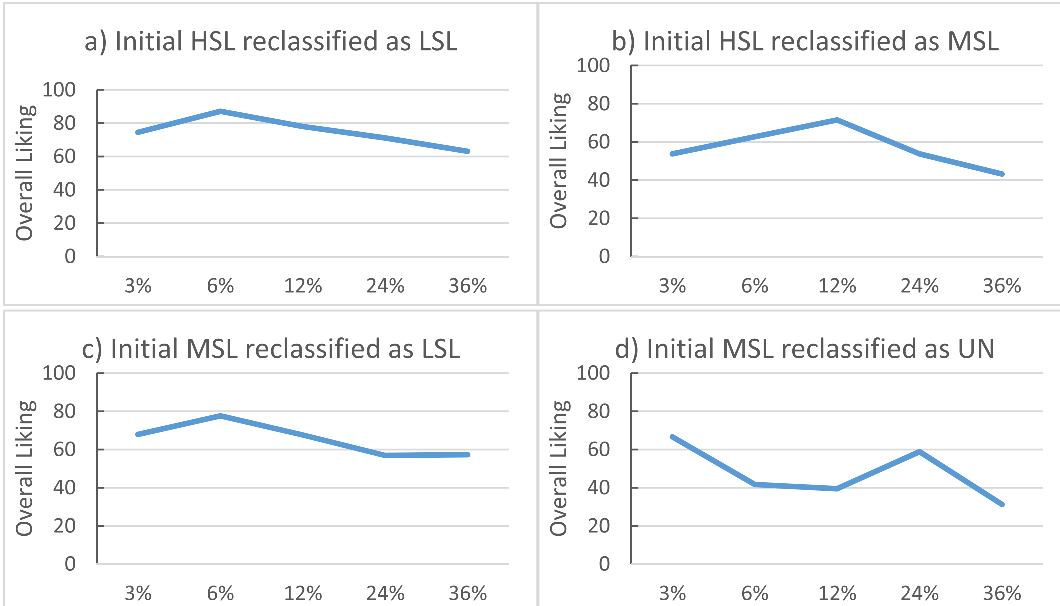

Fig. 2. Example of hedonic patterns of reclassified participants. The initial cluster was obtained using AHC analysis alone; participants were then reclassified using the validated method using correlation matrices base on Yang et al., 2019. HSL – High Sweet Liker, MSL – Medium Sweet Liker, LSL – Low Sweet Liker, UN – Unclassified.

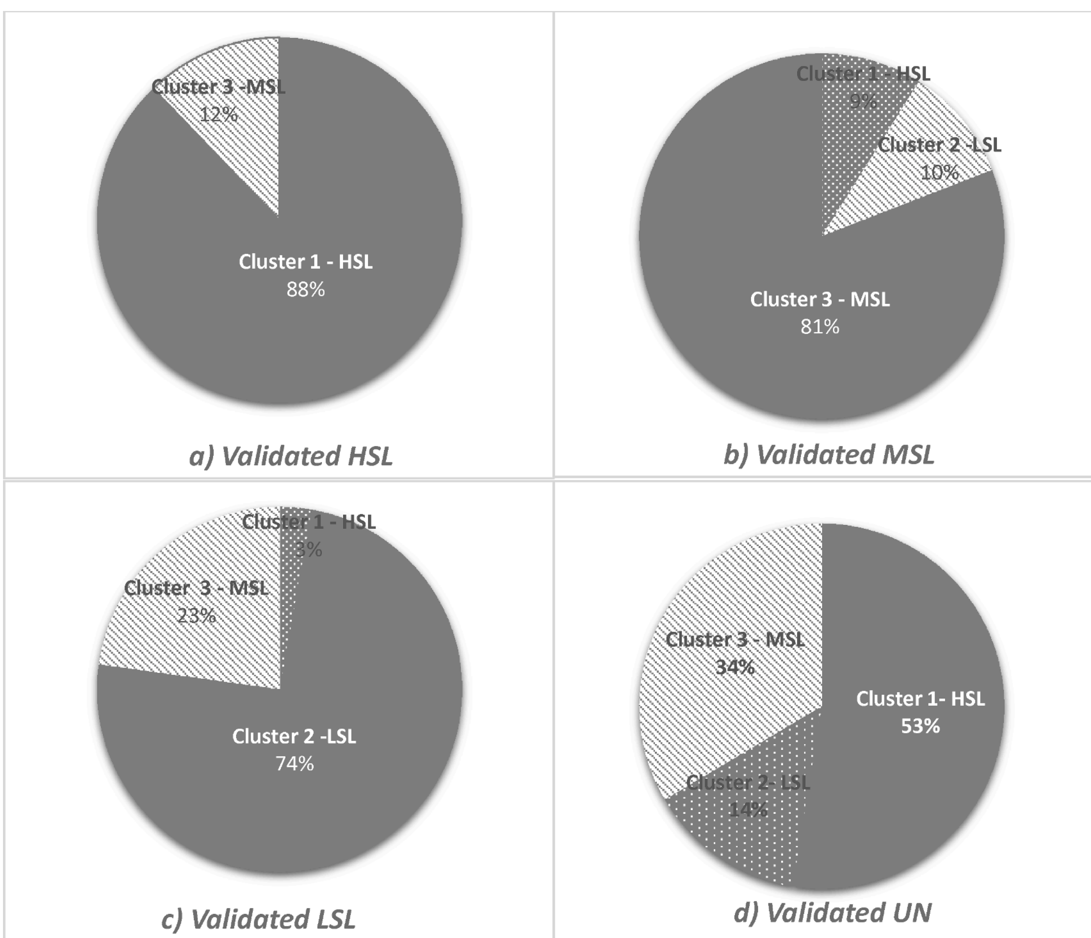

Fig. 3. The distribution of SLS clusters obtained from the initial AHC analysis (Cluster 1- HSL, Cluster 2- LSL, Cluster 3 – MSL) within the validated a) HSL, b) MSL, c) LSL and d) UN groups. Each validated SLS group is represented by an individual pie chart, containing the percentage (%) of initial AHC clusters.

% of the total participants. After the reclassification, four validated SLS clusters were identified: 230 participants (27 %) as HSL, 157 participants (18 %) as MSL, 320 participants (37 %) as LSL, and 158 participants (18 %) classified as UN. As shown in Fig. 3, 88 % of *validated HSL* were from Cluster 1 (HSL), 12 % were from Cluster 3 (MSL), and none were from Cluster 2 (LSL) (Fig. 3a). For *validated* MSL, 81 % were Cluster 3 (MSL), 10 % were Cluster 2 (LSL) and 9 % were Cluster 1 (HSL). For *validated LSL*, 74 % were Cluster 2 (LSL), and 23 % were Cluster 3 (MSL), and 3 % were Cluster 1 (HSL) (Fig. 3c). It is worth noting that a significant number of participants (n = 158) were assigned to the *validated UN* group (53 % Cluster 1, 34 % Cluster 3, 14 % Cluster 2) since they showed inconsistent liking responses across the five sucrose solutions which might not be taken into account using AHC analysis alone.

As shown in Fig. 1, applying AHC alone resulted very different SLS cluster groups across the seven studies, making it difficult to directly compare results. Concordance analysis was conducted between AHC and validated classification method for each individual study. Concordance was poor for study 4 ($\kappa = 0.199$), fair for study 2 ($\kappa = 0.314$), study 3 ($\kappa = 0.254$), and study 7 ($\kappa = 0.228$), moderate for study 1 ($\kappa = 0.581$), study 5 ($\kappa = 0.407$) and study 6 ($\kappa = 0.412$). For the combined dataset overall concordance was moderate ($\kappa = 0.527$), with moderate concordance for MSL ($\kappa = 0.452$), and good concordance between HSL ($\kappa = 0.642$) and LSL ($\kappa = 0.694$). Concordance was poor for UN ($\kappa = 0.000$) as AHC did not classify any individuals in that group.

Although the validated method following Yang et al. (2019) could improve SLS classification, this approach relies on reliable mean liking scores for HSL, MSL and LSL. Therefore, the recommendation is to directly apply the correlation matrix between each individual's liking scores and the *validated HSL*, *MSL* and *LSL* liking scores (shown in Table 1). Individuals should be assigned to SLS clusters based on the highest correlation coefficient, with minimum correlation coefficient value set at 0.6. Participants showing weak correlation with HSL, MSL or LSL clusters ($r < 0.6$) should be assigned to the Unclassified (UN) group.

3.2. Rapid three-solution method

Due to growing interest in rapid taste phenotype classification, this study explored a simplified method of applying correlation matrices to the liking scores of three solutions (3 %, 12 % and 36 % sucrose) instead of all five solutions (3 %, 6 %, 12 %, 24 % and 36 %). Similar to the five-solution classification method, correlation matrix was applied between participant's liking scores for the three solutions and the validated liking scores for HSL, MSL and LSL as shown in Table 1. As demonstrated in Fig. 4, the rapid three-solution method was able to successfully identify 97 % of the *validated HSL*, 87 % of *validated MSL* and 78 % *validated LSL* of the validated five-solution method. However, using the rapid three-solution method, 35 % of the participants from the *validated UN* group were assigned to the HSL cluster, 23 % were assigned to LSL and 17 % were assigned to MSL. Overall, good concordance was found between the two methods ($\kappa = 0.667$). Concordance was highest for HSL (excellent, $\kappa = 0.839$), followed by LSL (good, $\kappa = 0.690$), MSL (good, $\kappa = 0.630$) and UN (fair, $\kappa = 0.355$). These data suggest that the rapid three-solution method was able to successfully identify the majority of HSL, MSL and LSL within the dataset. However, 72 % of the *validated UN* group were misclassified, inaccurately assigning consumers to HSL, MSL or LSL groups.

When exploring the perceived sweetness intensity ratings, both methods revealed a significant SLS effect ($p < 0.001$). Post-hoc tests revealed a significant difference between HSL and LSL ($p < 0.001$) for both methods (Fig. 5). The validated five-solution method also found that LSL rated the perceived sweetness of sucrose solutions significantly higher than MSL ($p = 0.008$), however, no such difference was observed when using the rapid three-solution method ($p = 0.08$).

Table 1
The mean liking scores for validated HSL, MSL and LSL.

	3 % Sucrose	6 % Sucrose	12 % Sucrose	24 % Sucrose	36 % Sucrose
HSL	46.2	56.8	68.6	72.3	71.9
MSL	51.3	60.9	69.0	59.3	38.5
LSL	59.8	60.0	51.1	32.8	28.1

4. Discussion

Due to different sucrose concentrations and inconsistent classification methods used in previous research summarised by Iatridi et al., 2019, it is not surprising that the proportion of HSL reported across different studies varies significantly (from 12 % to 78 %) (Garneau, Nuessle, Mendelsberg, Shepard, & Tucker, 2018; Pangborn, 1970; Yang et al., 2019; Yang et al., 2020). More recent studies (Kim et al., 2017; Yang et al., 2019) have adopted AHC analysis to cluster SLS as a far superior method over the visual pattern classification (Yeomans et al., 2007), 'average above mid-point' approach (Methven et al., 2016) and paired preference approach (Mennella et al., 2014). However, as demonstrated by the present study, if used on its own, AHC can lead to conflicting findings in terms of number of clusters and hedonic patterns, limiting its effectiveness as a standardised method. Inconsistent SLS clusters with notably different hedonic patterns were observed across the seven different studies conducted at the University of Nottingham as a result of AHC analysis alone (Fig. 1), thus, making the data comparison between studies challenging. Previous research reported associations between ethnicity, gender and SLS, where Asians are more likely to be LSL, and males are more likely to be HSL (Yang et al., 2020). Therefore, if the demographic composition of participants is different across studies, AHC is likely to produce very different clusters. For example, participants in Study 6 were Caucasians only (Fig. 1d), whereas participants in Study 7 were Chinese only (Fig. 1e). These data highlight the importance of using a standardised classification methodology that would allow data comparison among different studies regardless of sociodemographic variables and improve the efficiency of the SLS clustering process. Yang et al. (2019) has suggested applying AHC followed by a correlation matrix to improve the robustness of SLS classification. However, the robustness of this method solely relies on the validated liking scores representing HSL, MSL and LSL. Therefore, the need to develop a statistically robust, efficient and universal classification method is evident, as highlighted by several recent studies (Iatridi, Hayes, & Yeomans, 2019; Yang et al., 2019, Yang et al., 2020).

In the current study, Yang et al. (2019)'s approach was used in order to classify participants into reliable SLS clusters. A large dataset of consumers (n = 865) was used to generate robust mean liking scores representing the three SLS groups (HSL, MSL and LSL, Table 1). Therefore, the recommendation for future studies is to directly apply the correlation matrix between each individual's liking scores with the validated HSL, MSL and LSL cluster mean liking scores, as shown in Table 1. This method is believed to provide a universal, robust and more efficient SLS classification.

With SLS commonly used as a screening tool for segmenting consumers to further understand food preference, emotional response, food intake, dietary habit and health-related matters, research calls for a more rapid classification method. To address this need, the rapid three-solution method using the hedonic data of only three sucrose solutions was explored in the present study. Generally, the rapid three-solution method was able to accurately classify the majority of HSL, MSL and LSL within the dataset, however, 72 % of participants from the *validated UN* group were misclassified and subsequently assigned to the other three SLS clusters. These discrepancies are unsurprising, since it is less likely to identify distinct hedonic patterns using only three data points.

In addition to variation in hedonic liking, significant differences in perceived sweetness intensity scores were identified between HSL and LSL classified using both the rapid and the validated methods, highlighting the differences in sweetness responsiveness between the

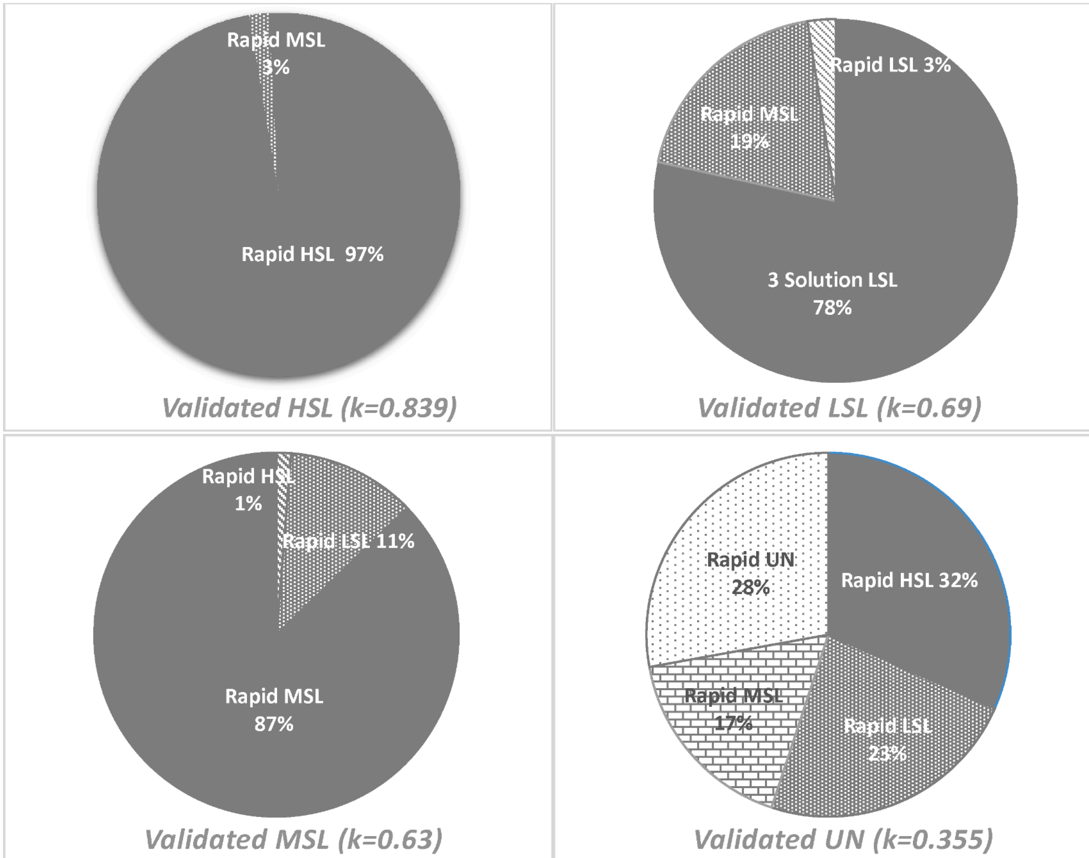

Fig. 4. The distribution of SLS clusters obtained using the Rapid three-solution method) within the validated (a) HSL, (b) MSL, (c) LSL and (d) UN (Validated five-solution method). *Each validated group is represented by an individual pie chart. k indicates Cohen's Kappa coefficient obtained to indicate agreement between Rapid method and validated method.*

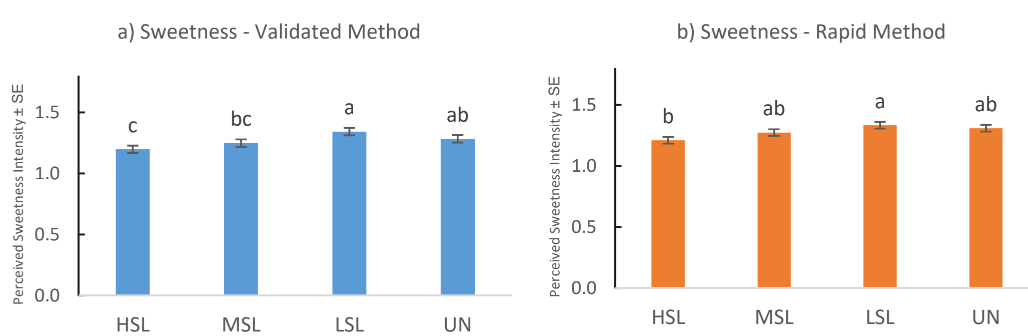

Fig. 5. Perceived sweetness intensity for (a) Validated five-solution method and (b) Rapid three-solution method. *Different letters indicate significant difference at $p < 0.05$.*

phenotype groups (Fig. 5). Despite the fact that MSL rated the sweetness of the solutions lower than LSL, as classified with both methods, the difference was not significant when using the rapid approach. This highlights that the rapid three-solution method is likely less precise than the validated five-solution method. Therefore, the rapid three-solution approach should only be used when a fast and convenient technique for classifying individuals is required and additional noise in the data can be tolerated. It is important to highlight that the two classification methods in the current study were based on the same dataset, and therefore more studies are needed to compare the validated and rapid classification methods by measuring consumers' liking responses separately to further validate the rapid SLS testing approach.

The concentration range selected for this study (0.087, 0.17, 0.35, 0.7 and 1.05 M) has commonly used to explore liking and emotional response to food/beverage varying in sweetness level (Methven et al., 2016, Kim et al., 2017, and Yang et al., 2019). Using the selected range of solutions, which subsequently represented a variety of different sweetness levels, participants demonstrated clear and distinct hedonic patterns. However, as highlighted by the review of Iatridi et al., 2019, sucrose concentrations used for measuring liking patterns vary greatly from study to study. Another commonly selected concentration range is 0.05, 0.10, 0.21, 0.42 and 0.83 M, often used to explore associations between sweetness preference and alcohol consumption (Bouhlal et al., 2018). Both concentration ranges have been shown to successfully classify individuals for SLS in previous literature. HSL and LSL have very distinct hedonic patterns for sucrose and therefore are less likely to be affected by the different concentration ranges used in different studies. The MSL cluster tends to show an inverted U liking pattern, with a decline in liking at the higher concentrations. Thus, MSL are more susceptible to SLS misclassification if high enough concentrations of sucrose are not included to capture the full range of liking. By using fewer concentrations, the rapid three-solution method discussed in the present study may be less effective at identifying MSL. More research is needed to understand the liking patterns of different SLS groups based on the number of sucrose samples presented and the concentration range selected. In addition, future studies should explore the robustness of SLS classification across different types of sugars including both natural and artificial sweeteners. Lastly, the findings of the present study suggest that the validated liking scores (Table 1) should be applied for more consistent and robust SLS classification when using the concentration range selected for this study (3 %, 6 %, 12 %, 24 % and 36 % w/v). However, at present these are limited for the use in aqueous solutions, and further research will be required to determine and validate hedonic patterns in other food matrices.

5. Conclusion

Sweet Liking Status phenotype is widely recognised as a type of taste-related individual variation. Despite this, methods used to classify participants for SLS vary widely, making it difficult to compare results across studies. Using a large sample (n = 865), the present study found that classifying participants using AHC alone can lead to around one third of individuals being misclassified. In addition, the data showed that sucrose liking patterns can vary significantly when AHC is performed on different cohorts. Thus, it is recommended that future studies adopt a correlation-based approach for SLS classification using the validated liking means for five sucrose solutions (3, 6, 12, 24, and 36 % w/v) provided in the current study. Finally, the results demonstrated a good level of agreement between the rapid three-solution method and the validated five-solution method for determining SLS, especially for HSL and LSL. However, additional research is needed to further validate whether the rapid three-solution method could provide a reliable SLS classification.

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.

Data availability

Data will be made available on request.

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