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Principles and Validations of an Artificial Intelligence-Based Recommender System Suggesting Acceptable Food Changes

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ABSTRACT

Background: Along with the popularity of smartphones, artificial intelligence-based personalized suggestions can be seen as promising ways to change eating habits toward more desirable diets.

Objectives: Two issues raised by such technologies were addressed in this study. The first hypothesis tested is a recommender system based on automatically learning simple association rules between dishes of the same meal that would make it possible to identify plausible substitutions for the consumer. The second hypothesis tested is that for an identical set of dietary-swaps suggestions, the more the user is—or thinks to be—involved in the process of identifying the suggestion, the higher is their probability of accepting the suggestion.

Methods: Three studies are presented in this article, first, we present the principles of an algorithm to mine plausible substitutions from a large food consumption database. Second, we evaluate the plausibility of these automatically mined suggestions through the results of online tests conducted for a group of 255 adult participants. Afterward, we investigated the persuasiveness of 3 suggestion methods of such recommendations in a population of 27 healthy adult volunteers through a custom designed smartphone application.

Results: The results firstly indicated that a method based on automatic learning of substitution rules between foods performed relatively well identifying plausible swaps suggestions. Regarding the form that should be used to suggest, we found that when users are involved in selecting the most appropriate recommendation for them, the resulting suggestions were more accepted (OR = 3.168; $P < 0.0004$).

Conclusions: This work indicates that food recommendation algorithms can gain efficiency by taking into account the consumption context and user engagement in the recommendation process. Further research is warranted to identify nutritionally relevant suggestions.

Keywords: behavior change, food recommendation algorithms, decision sciences.

Introduction

Changing eating behaviors is critical to ensure food systems that are both healthy and environmentally sustainable [1]. These changes are very difficult because eating habits are firmly rooted [2] and the resistance to changes is often strong [3, 4]. The use of computer-based recommender systems appears to be a promising strategy to change consumption behavior toward more desirable diets. Smartphones have become a personal assistant for many individuals, beyond simply allowing customers to search for product information, compare prices, and seek feedback; smartphone applications could use algorithms to provide users with personalized suggestions [5]. Such algorithms would interact with humans [6] to propose a series of punctual substitutions [7], new recipes, or entire meals [8] and thus move individuals toward healthier diets through small iterative changes. Research in this field of application is still largely incomplete and among the many research questions to be addressed in food recommendation technologies. The consumer acceptability of recommender systems relies on: *1)* the user's compliance with the machine and *2)* the relevance of its suggestions. Therefore, 2 questions seem particularly salient: first,

Abbreviations used: AI, artificial intelligence; INCA2, *Étude Individuelle Nationale sur les Consommations Alimentaires 2006–2007* (National Individual Food Consumption Study 2006–2007).

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what should the artificial intelligence (AI) suggest? Second, *how* should the AI suggest? This question concerns the form of human-computer interaction that is most likely to ensure user compliance.

A first difficulty is that eating decisions are complex processes [9] influenced by numerous and intricated factors, such as individual preferences, social influences, or contextual effects [10–14], and they all display a strong variability across individuals [15] or groups [16]. Identifying acceptable recommendations will therefore require an understanding of how one or several of these factors shape acceptability [17, 18]. Although the literature on how acceptability is driven [19], either by individual preferences, food variability and dynamics, or the effects of the social context is rather extensive, few studies have focused on the rules governing the meal composition. A meal or a menu is not just a random arrangement of foods, it is a complex assembly that often complies with very strict rules of associations or exclusions among food items. Because the deduction of such rules by a human observer would be very limited, machine learning algorithms could be used to explore large volumes of consumption data to come up with relevant suggestions. The first hypothesis tested is that a recommender system based on automatically learning simple association rules between dishes of the same meal would make it possible to identify plausible and acceptable substitutions from a consumer standpoint.

Finally, considering that the acceptability of a suggestion varies depending on how it is presented to users, identifying the most persuasive recommendation method is an essential issue. Several directions have so far been explored, such as personalization [20], gamification [21] but also the engagement of the user in the selection process [22]. The questionable effect of user engagement on acceptability is an open question. Indeed, 2 opposite hypotheses can be formulated. It can be argued that receiving a recommendation without much effort can be perceived as comfortable and attractive to the user thus favoring his or her future acceptability. Conversely, it can be assumed that if the user feels that he or she has control over the suggestions, he or she will be more inclined to accept them in the end. The second hypothesis tested is that for an identical set of dietary-swaps suggestions, the more the user is—or the more the user thinks to be—involved in the process of identifying the suggestion, the higher is their probability of accepting the suggestion.

In this article, we present 3 studies related to the testing of these hypotheses. The first 2 studies are related to our first hypothesis about the validity of automatic identification of food recommendation, whereas the last work focused on the hypothesis formulated above on the most effective form of the recommendation. First, we present the principles of a method to reveal relevant substitutions from a large food consumption database. Second, we evaluate the plausibility of these automatically mined suggestions via online tests. Afterward, we investigate the persuasiveness of 3 suggestion methods of such recommendations in a population of healthy volunteers.

Methods

Design and implementation of an algorithm able to identify relevant substitutions

Problem statement and objectives

Our first objective was to develop an algorithm with an ability to mine substitutable foods. Given a database of consumed meals, we aimed to extract substitutability relationships based on the implicit rules applied by consumers when they compose their meals. The hypothesis on which we based our mining method of relevant substitutions was that "*2 food items are substitutable if they are consumed in a similar dietary context but rarely together*." A detailed description of this algorithm has been realized and was the subject of a previous publication [23].

Defining context

The dietary context of a food item x is the set of food items C with which x is consumed. For instance, in the meal (*coffee*,*bread*, *jam*,*juice*), the dietary context of (*coffee*) is (*bread*,*jam*,*juice*)

Computing a substitutability score

Substitutability is not a binary relationship because foods can be substituted to various extents. For instance, it is plausible to replace potatoes with rice, less plausible to replace them with bread, but much less plausible to replace those same potatoes with ice cream. Moreover, if 2 items are consumed together, they are less substitutable because they might be associated. Therefore, we designed a function to quantify the relationship of substitutability that incorporates the possibility of associativity. Detailed computing of the substitutability score are presented in **Supplementary Methods**.

Mining of relevant substitutions

The French dataset INCA2 [24] was used for the mining of relevant substitutions. This dataset is the result of a survey conducted during 2006–2007 on individual food consumption. Individual 7-d food diaries were reported for 2624 adults and 1455 children over several months accounting possible seasonality in eating habits. It should be noted that since the start of this study, which was the subject of an initial communication, another more recent survey has become available [25]. Because the results of the search for substitutability differed little over this period of time, we preferred to maintain consistency with the initial study. A typical day was composed of 3 main meals: breakfast, lunch, and dinner. The moments in between were denoted as snacking. For the main meals, the location (home, work, school, and outdoor) and the companion (family, friends, coworkers, and alone) were registered. The 1280 food entries were organized in 110 groups of food items. We chose to consider this *subgroup* level of hierarchy to capture intergroup and intragroup substitution relationships. Indeed, it would have been possible to choose a finer categorization (more groups) but this would have led to the identification of only substitutions between very similar subgroups. On the other hand, we could have chosen a coarser categorization (fewer groups), but this would have greatly constrained the algorithm's searches. The level of grouping chosen was thus determined to obtain the best compromise between very relevant but closely related changes and important but not very relevant changes. Only adults are considered in this work. The meal database was split according to contextual (type of meal) information to get better results. We compared the results of our methodology on 3 sub datasets corresponding to (breakfast, lunch, and dinner) as well as (breakfast and lunch and dinner).

Evaluation of the plausibility of substitutions mined by the recommendation algorithm

To evaluate the extent to which the algorithm was able to generate plausible substitutions suggestions, an online task was designed in the manner of a *Turing test* [26] in which participants were asked to guess whether the proposed food substitutions were issued by either AI or by a human being.

Participants

Volunteers were invited to participate in an online experiment via a public mailing list run by the French National Centre for Scientific Research (Information Relay in Cognitive Sciences, Paris, France, www.risc.cnrs.fr). The inclusion criteria were to be >18 y of age and to be able read and understand French language properly. Participants could not participate more than once. On completion of the experiment, participants could enter in a draw Q8 to win 15€. A total of 255 participants were included in the study, none of them reported to have guessed the objective of the study.

Online task

The experimental task consisted of 3 presentations of a series of 12 meals for which a proposal for change was made. Proposals were made either by a professional dietician or by the substitution mining algorithm. In the latter case, to test the relevance of the substitutability scoring system, algorithm suggestions either reflected substitutions with the highest substitutability score (expert algorithm) or substitutions with a low substitutability score (clumsy algorithm). All these suggestions concerned the same items of the 12 same meals. For each pair of meal + modified meal, participants had to answer (*yes* or *no*) to the following question: "*some of these suggestions are made by an AI, others by a dietician, do you think this substitution was made by an AI?*" The supporting software was developed using the *Penn Controller for Internet Based Experiments* platform [27].

Data analysis

The dependent variable is the binary answer to the question on the emitter of the substitution recommendation (human/nonhuman). Binary logistic regressions and resulting OR were used to evaluate whether the answer was influenced by the actual type of emitter.

Acceptability of identified recommendation on a group of volunteers

This work examined whether the extent of user involvement in the suggestion process substitutions by the AI-based recommender system affects the acceptability of that suggestion. For this purpose, a food coaching interface based on the plausible substitution mining algorithm presented earlier was tested on participants. These participants were different from the volunteers of the previously described online study. Q9

Ethics approval. The study was conducted according to the Helsinki declaration guidelines and all procedures were approved by the Ethics Committee of Université Paris-Saclay (decision CER-Paris-Saclay-2021-055). Written informed consents were obtained from all the participants. Access to the *General Data Protection Regulation* is permanently available from the application interface. The participation in the experiment was compensated by a gift voucher worth 50€.

Participants

Based on similar studies [18, 23, 24, 28], we estimated that 30 volunteers were needed for this study. Considering a dropout and noncompletion rate of the experiment of 50%, to obtain ~30 complete and exploitable responses, 60 candidates were recruited. The recruitment was done through an online form distributed via a public mailing list run by the French National Centre for Scientific Research (Information Relay in Cognitive Sciences, Paris, France, www.risc.cnrs.fr). The inclusion criteria included being >18 y old, not being on a diet, and owning a smartphone. To avoid possible effects of the order of presentation, the participants received the different modalities in a random way.

Operation of the algorithm

A smartphone application (virtual nutrition coach) was specifically designed for this study. The principle was as follows: *1)* the participant declares the meal they intend to eat the next day to the virtual coach. *2)* The virtual coach makes a substitution suggestion targeting one of the items of the meal according to the 3 modes of suggestion (detailed below). *3)* The participant can either accept or refuse the suggestion(s). *4)* If they accept, they commit to implement the recommendation and to certify it by sending a picture of their meal via the mobile application. For 1 declared meal made by the user, 4 suggestions were identified by the virtual nutrition coach through an online query to the substitution mining algorithm (described above), the list of these possible substitutions was based on the 4 most substitutable items presenting a better nutritional profile [according to their Rayner's score [32]]. The 3 modalities were as follows: *1)* all 4 options were presented simultaneously, and the user could choose either one or nothing. *2)* identified options were presented one by one, and each time the user could refuse (in which case they must justify their refusal) until the list of proposals exhausted, if the last proposal was not accepted then no option was chosen. *3)* The coach asked the user for their preferences and proposed a single dish, which best matched the announced criteria. The user could either accept or refuse.

Measured parameters

At the beginning of the experiment, the volunteers filled out a questionnaire indicating their age, sex, and BMI. For each recommendation session, the acceptance or refusal data were recorded, as well as the constituents of the meals filled in by the volunteers and the elements suggested by the coach.

Data collection procedure

The study used a within-subject design to test 2 meal conditions. The experiment lasted 3 weeks, spanning June and July

2021. During the sessions, the recruited volunteers had 6 recommendation sessions every Tuesday and Thursday, during which they received a suggestion that they could accept to implement the next day. These 6 sessions were divided into 2 sessions for each of the recommendation methods.

Statistical analysis

To explain the influence of the mode by which the recommendation is given on the probability of acceptance, a binary logistic regression analysis has been implemented. The statistical model used is therefore described as follows:

$$p(accept) \sim sex + method + sessionnumber + age + BMI$$

All statistical analyses were performed by using R (version 3.6.3) and R-Studio (RStudio 2021.09.1+3"2 "Ghost Orchid" Release). To represent the probabilities of acceptance, ORs were computed from the logistic regression model.

Results

Identification of substitutions

Applied to the 3-meals datasets (breakfast, breakfast and lunch, and lunch), the algorithm retrieved a series of substitutable items for all considered items in the database. Substitutable items for each element of a list of items for breakfast are represented in Figure 1. If substitutions across food categories turned out to be proposed by the algorithm, the most frequent substitutable items were intracategory substitutions. When considering all foods listed in the consumption database, on average 6% of all retrieved substitutions were within the same food category, this proportion increased to 20% when only considering the 3 most substitutable items for each food. The substitutions proposed were also consistent with regards to the eating practices; substitutes of drinks were also drinks: 54% if considering all substitutions; 100% when considering 3 most substitutable items (e.g., the substitutes of coffee were tea, cocoa, and chicory) or the substitutes for butter for breakfast were spreadable items (26% compared with 100%). Detailed description of the results obtained by this algorithm was provided and was the subject of our previous publication, particularly, the comparisons between substitutability scores according to the meals [23].

Plausibility of mined substitutions retrieved by the algorithm

A total of 255 participants participated in the study, none of them reported to have guessed the objective of the study. When comparing human and AI recommenders, we found that the probability that participants judge recommendations made by a human to be *made by nonhumans* was low (0.26 $\pm$ 0.01), whereas the probability that participants judge recommendations made by an AI (clumsy and expert) to be *made by nonhumans* (0.67 $\pm$ 0.01) this difference appeared as highly statistically significant at $P < 10^{-16}$. When comparing the 2 AI-based emitters (clumsy compared with expert), we observed that a recommendation made by the *clumsy* AI had a significantly higher chance of being judged as not emitted by a human (0.71 $\pm$ 0.01) than a recommendation made by *an expert* (0.64 $\pm$ 0.01), here again this difference appeared as highly statistically significant at $P < 10^{-10}$

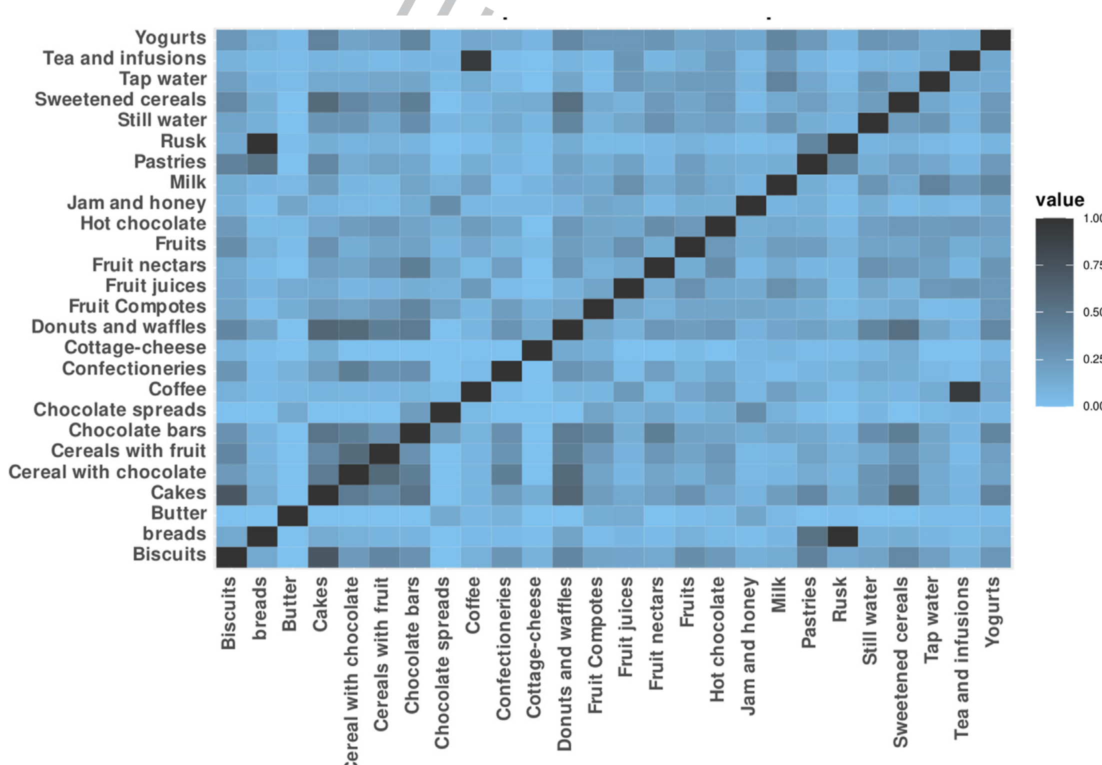

FIGURE 1. Substitutability scores computed between most frequent breakfast items. The breakfast subdataset was extracted from the French dataset INCA2 [24] gathering individual 7-d food diaries were reported for 2624 adults and 1455 children.

Real-life acceptability of identified suggestions and effect of recommendation methods

Of the 60 candidates initially enrolled in the experiment, the results of 27 of them were complete and exploitable for analysis (yielding a total of 162 meals). The final sample was composed of 20 women and 7 men. The mean age was 37.5 ± 15.2 y. The mean BMI was 22.2 ± 4.1 with 2 overweight individuals and 2 others moderately obese. Of the 162 interaction outcomes between the participants and the coach we observed that 74 interactions resulted in the acceptance of a recommendation, reflecting an overall average acceptability of 46%.

Analysis of the ORs corresponding to the different factors of influence of the acceptability revealed that modality B only, (i.e., when the user is participating to the selection of the suggestions, OR: 3.168; 95% CI: 1.688, 6.061; $P < 0.0004$) was associated with an OR exceeding the significance threshold. A tendency was noted for the effect of age ($P = 0.08$) indicating that younger participants had a higher propensity to accept recommendations. Sex ($P = 0.14$) and BMI ($P = 0.32$) did not have a significant effect on acceptability.

Discussion

This work presents an AI-based food recommendation system designed to make suggestions of food substitutions to its users. Two critical issues raised by such a recommendation technology were addressed in this study: first, the method to identify relevant substitutions suggestions and, second, the most efficient form that should be used to ensure acceptability from users. To identify acceptable substitutions, we hypothesized that 2 foods consumed with the same other foods can be replaced by each other with a relatively high probability of acceptance. Our results indicated that such a method, based on the analysis of a large-scale food consumption database and without any prior information of the considered dishes, showed overall coherence because the suggested swaps were often within the similar food types. We also found that such mining of relevant substitutions based solely on the analysis of the meal context, allowed to produce plausible suggestions from a human perspective. Regarding the form that should be used to suggest a substitution, our results obtained from a group of 27 volunteers over a period of 3 wk suggest that when users are involved in the selection of suggestion, the resulting suggestions are more likely to be accepted.

The substitutability score presented in this study was based on the estimation, for 2 foods to be substituted, to what extent these items are consumed in similar meals (i.e., with the same other foods). Although no semantic information describing ingredients or usual positioning of foods in meals was available for the recommender system, substitutions between food items of the same nutritional food groups were found. Such contextual information appears to be relevant to derive food substitutions. To our knowledge, this is the first study showing the richness of the information contained not in what we eat but in what we combine with what we eat. A substantial amount of research has already been performed in the area of recommendations to induce behavioral changes [7, 8, 18, 33], most existing approaches focused on recommending similar foods (with similar taste for instance) to consumers without considering any additional contextual information. By showing that such information may matter in the acceptability decision, we believe that we are opening a promising field of research for automated dietary recommendations. The main strength of this study is that it links fundamental algorithmic considerations related to the dietary decisions with studies on healthy volunteers in online or real-life consumption conditions.

Nevertheless, this work has focused on identifying solutions that are acceptable to the consumer. In this context, we have chosen to study the plausibility of the identified solutions only from the consumer's point of view, without trying to identify changes leading to a better nutritional quality diet. However, it is obvious that such technologies, to be really effective on improving the quality of diets, will have to integrate additional filtering rules allowing to select, among the plausible suggestions, only the foods improving the quality of the diet. For this purpose, scores taking into account past food consumption history could be used [34].

Additional limitations are that food swaps recommendations issued by this work cannot be generalized because the data set was collected in France and may not be relevant for other countries. Additionally, because the dataset was obtained during 2006–2007, the substitution relationships are likely to have changed along with the modification of the food offer, for example, an increase in plant-based meat substitutes would require new data on their consumption relationships. Future work will need to address these limitations.

In a second step, using a task in which participants were invited to judge whether the emitter of a given suggestion was a human or a machine, we observed that recommendations made by AI were often recognized as originating from a nonhuman recommender. This indicates that there is a margin of progress in our ability to derive substitutability information from food consumption databases. Interestingly, we observed that depending on the substitutability scores chosen by the AI for selecting a recommendation (best scores or weaker scores), the participants estimated differently the plausibility of the resulting suggestions, because a high score was associated with a low probability of judging the emitter as nonhuman. This substitutability score is thus a promising but perfectible proxy of the acceptability of substitutions. To gain predictive capacity, it could be useful to extend the concept of *contextual information* to include other information that is known to influence eating decisions, such as the consumptions made at the preceding meals, the time and/or the location [9, 35] of the meal, or the company of others [36, 37].

However, it is important to be cautious when interpreting these results. We indeed assumed that the criteria on which participants based their responses was the plausibility of the suggestion (e.g., "*if I think it is a non-sense, it must have been issued by a machine*"). However, it cannot be excluded that the participants' responses were based on other criteria. The reasoning that they would attribute to the machine (e.g., "*the recommender is expected to make recommendations being of high nutritional quality, if it is not the case it must be a machine*") could strongly influence the results. It would thus be interesting to combine these approaches with qualitative measures in which explanations of the reasons for the choices indicated in the task would be recorded.

In a third step, we showed on a cohort of 27 participants that among the 3 modalities of suggestion presentation, the one that seemed to have the highest efficiency was the one that involved the user in repeated exchanges, and even if the suggested options were the same as what would have been offered by the other modalities, the impression of dialogue and thus of control over the production of recommendation yielded greater acceptability from the consumer. In the field of recommender systems, such an approach is called critiquing-based recommendation because it relies on users' feedback (critiques) to iteratively improve the recommendation's acceptability. The advantage of such an approach can be explained by the illusion of control that individuals may have in the case of a critiquing-based system. Indeed, studies in psychology or behavioral economics on the endowment effect, popularly known as the IKEA effect [38, 39], have established that the more we engage in a task (in this case, finding a consumption suggestion), the more we are attached to the result, and the greater the value of this result is for us.

The critiquing-based recommendation modality system has emerged as the most acceptable, it is interesting to note that this performed even better than modality C, which registered preferences before making a recommendation. This advantage could be explained by the fact that when user's preferences-based recommender systems have little information about the users they often fail to establish a meaningful profile (cold start problem [40]). Conversely, it is likely that if virtual coaches had access to large amounts of data on user preferences, they would be more effective than critiquing-based coaching modalities.

However, such results should not be generalized because the profile of the participants remains not representative, being constituted mainly by young women. The number of participants and the design of the study did not allow to identify different profiles; however, if the modality based on *critiquing* seems to be more effective, we cannot exclude that another modality would be more effective in inducing behavioral changes for some subgroups.

In conclusion, although computerized recommender technologies may be a promising tool for changing eating behaviors, several questions remain open. First, concerning the methods for selecting acceptable alternatives, we proposed a substitutability score based on a limited amount of contextual information (i.e., foods eaten with the food to be substituted) and showed that it can be used to identify plausible and acceptable alternatives. This is a promising approach, but it is highly perfectible and will gain in quality if we consider other contextual elements in the substitution retrieval method. Second, the interactions between the recommendation technologies and the users are another facet determining the acceptability that it is necessary to consider. We have highlighted that approaches involving the users seem to have an advantage, but this work remains to be refined by putting into perspective the individual profiles and the most effective suggestion modalities. Future research should therefore focus on understanding the dynamics of consumption (recent food history, for example) and on the effects of the diversity of consumer profiles on the types of human-machine interactions to consider. Finally, additional work will also have to take into account the nutritional quality of the suggested swaps to improve overall diet quality.

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Uncited references

[29], [30], [31].

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Author contribution

The authors' responsibilities were as follows – JV: methodology, investigation, formal analysis, visualization, writing–original draft; P.H: methodology, investigation; MK: methodology, investigation; PV: conceptualization, methodology, validation; LM: conceptualization, methodology, validation; ChM: conceptualization, methodology, validation; OD: methodology, conceptualization; CrM: conceptualization, methodology, validation; AC: supervision, conceptualization, methodology, formal analysis, writing–original draft. ND: supervision, project administration, funding acquisition, conceptualization, methodology, formal analysis, writing–original draft and reviews. All the authors participated in writing–reviewing and editing. All authors have read and approved the manuscript. Support to this study is exclusively from governmental entities.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tjnut.2022.12.022.

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