Health Claims Unpacked: A toolkit to Enhance the Communication of Health Claims for food

Xiao Li
The University of Reading
xiao.li@reading.ac.uk

Huizhi Liang
The University of Reading
huizhi.liang@reading.ac.uk

Zehao Liu
The University of Reading
zehao.liu@reading.ac.uk

ABSTRACT

Health claims are sentences on the food product packages to claim the nutrition and the benefits of the nutrition. Consumers in different European contexts often have difficulties understanding health claims, leading to increased confusion about and decreased trust in the food they buy. Focusing on this problem, we develop a toolkit for improving the communication of health claims for consumers. The toolkit provides (1) interactive activities to disseminate knowledge about health claims to the public, and (2) an NLP-based analysis and prediction engine that food manufacturers can use to estimate how consumers like the health claims that the manufacturers created. By using the AI-powered toolkit, consumers, manufacturers, and food safety regulators are engaged in determining the different linguistic and cultural barriers to the effective communication of health claims and formulating solutions that can be implemented on multiple levels, including regulation, enforcement, marketing, and consumer education.

CCS CONCEPTS

• **Human-centered computing** → *User interface design*; • **Computing methodologies** → **Probabilistic reasoning**; **Learning to rank**; • **Applied computing** → **Business intelligence**.

KEYWORDS

Attractive; Health Claim; Learning-to-Rank; Interface design

ACM Reference Format:
Xiao Li, Huizhi Liang, and Zehao Liu. 2021. Health Claims Unpacked: A toolkit to Enhance the Communication of Health Claims for food. In *Proceedings of the 30th ACM International Conference on Information and Knowledge Management (CIKM '21), November 1–5, 2021, Virtual Event, QLD, Australia.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3459637.3481984

1 INTRODUCTION

Health claims (HCs) are sentences on the food product packages to claim the nutrition and the benefits of the nutrition of food products, e.g. *Vitamin B6 contributes to the normal function of the immune system.* Food manufacturers are increasing including HCs on their packages [4]. Recent research shows that the presence of such claims on packages generally has a positive impact on consumers' perceptions of the healthiness of products and their willingness to buy them [7]. Consumers in different European contexts often have difficulties understanding HCs on food packages, leading to increased confusion about and decreased trust in the food they buy [9]. So, European Commission (EC) Regulation 1924/2006 was designed to increase consumer trust and promote healthy food choices by regulating the kinds of HCs. Although, Regulation (EC) 432/2012 encourages manufacturer presents more acceptable HCs to consumers that has "the same meaning" as permitted HCs, consumer confusion and mistrust continuously persist, as documented in a range of academic studies [1, 5, 6].

This continuing project [1] [2] is under the policies applied to all EU countries (while US shares the similar regulations). It aims to solve this problem by engaging consumers, manufacturers and food safety regulators in determining the different linguistic and cultural barriers to the effective communication of HCs and formulating solutions that can be implemented on multiple levels, including regulation, enforcement, marketing, and consumer education.

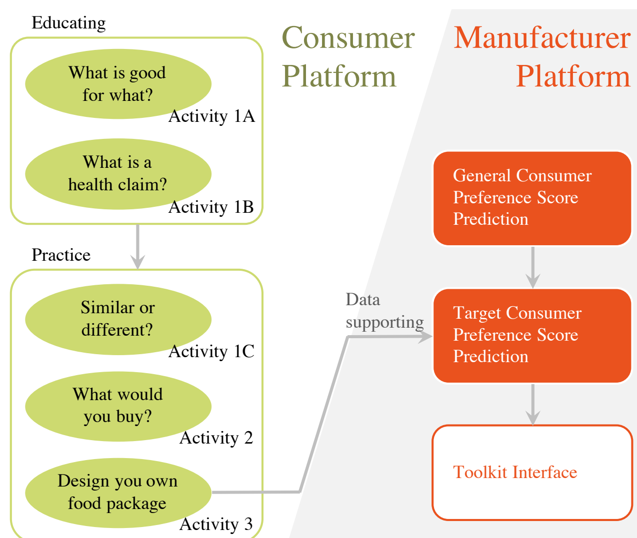

Figure 1: The general framework of the toolkit.

Since there is no open tool/service focusing on HCs, as the first stage of the project, in this paper, we propose and implement a digital toolkit – "Health Claims Unpacked". The toolkit plays the role of information collection, management and retrieval of HCs. On one hand, the toolkit engages consumers in a variety of activities designed to inform/educate consumers. These activities also

CIKM '21, November 1–5, 2021, Virtual Event, QLD, Australia

ACM ISBN 978-1-4503-8446-9/21/11…$15.00
https://doi.org/10.1145/3459637.3481984

[1] Project website: https://www.healthclaimsunpacked.co.uk/
[2] Toolkit website: https://www.unpackinghealthclaims.eu/

contribute to collecting data from consumers about their understanding and preferences of HCs for research purpose.[3] On the other hand, it conveys the data to facilitate an NLP and machine learning-based analysis and prediction engine to help food manufacturers to evaluate their created HCs in an automatic way.

2 UNPACKING HEALTH CLAIMS: THE TOOLKIT OVERVIEW

The toolkit mainly consists of two platforms – the consumer platform (see § 3) and the manufacturer platform (see § 4). The general framework of the toolkit is shown in Figure 1. The consumer platform aims to popularise the role, constitution, and importance of HCs to reduce consumer confusion and build up their trust in food products. It provides multiple interactive online *activities* including educating activities (Activity 1A, Activity 1B), and practice activities (Activity 1C, Activity 2, Activity 3 in Figure 1) to teach HCs knowledge to consumers. While the toolkit conveys the knowledge to the users, it tests the users' understanding as well as letting the users practice the knowledge. There are multiple perspectives to the users to understand HCs.

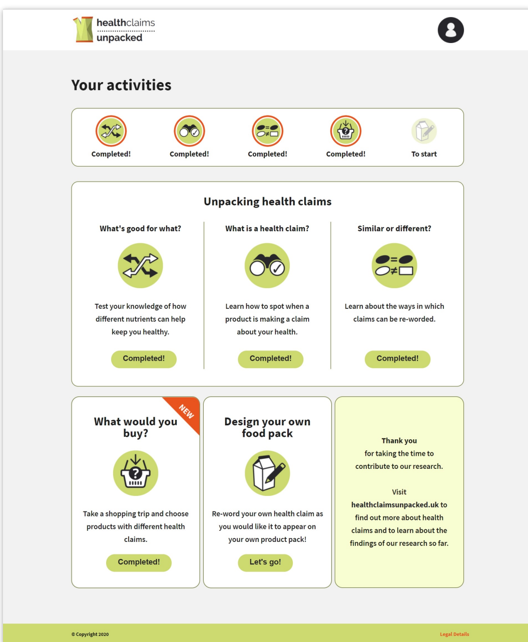

Figure 2: Consumer Platform Landing Page

In addition, the user responses in the practice activities (especially Activity 3; see § 4 for the details) are collected as an important source for learning the consumer preference to the HCs. The manufacturer platform aims to support the food manufacturers to evaluate their created HCs. By learning the consumer preferences from the collected data, there are two NLP-based prediction models in the manufacturer platform. They predict how much consumers like the HCs with 5-scaled scores for two different scenarios. The first model predicts the *general consumer preference scores*, which reflects the preference of the population (i.e., the first scenario). The second model is a conditional model, which predicts the *target consumer preference scores* – the preference of consumers that the consumer characteristics (e.g. gender, age, etc.) are specified by the platform users (i.e., the second scenario).

[3]Note: The collection, storage, and usages of data follow the guidance of the General Data Protection Regulation (GDPR).

Figure 3: Activity 1A: 'What's good for what?'

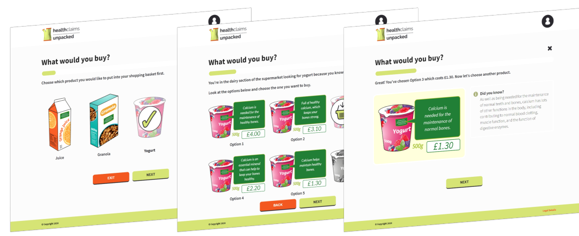

Figure 4: Activity 2: 'What would you buy?'

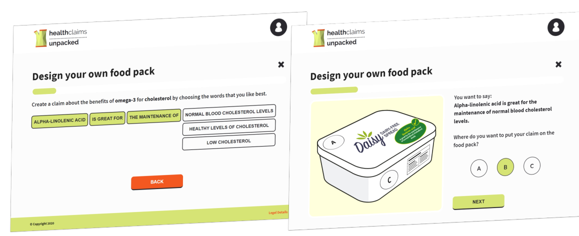

Figure 5: Activity 3: 'Design your own food pack'

3 CONSUMER PLATFORM IMPLEMENTATION

The consumer platform consists of two types of activities following the sequence of educating-practice. A user needs to register before using the platform, and the registration process including to ask the anonymous characteristic information (e.g. gender, age, etc.). In the landing page after the registration (Figure 2), it shows all the activities with users' learning progress. Each activity can be unlocked after the prior activity completing.

The educating activities adopt a teaching strategy of learning-from-testing. Activity 1A (*What's good for what?*) tests the user's knowledge of how different nutrients can help stay healthy at the very beginning. Users need to match nutrients to the health benefits (e.g. *Calcium* to *Digestion*). It gives users unlimited chances to find the correct answer, and the corresponding explanations show up subsequently to present the knowledge.

Activity 1B (*What is a health claim*) educates users on how to spot HCs on food packages and what are the legal HCs. Three examples are shown before the test begins for demonstrating. Then, in each question, a sentence including a nutrient is given; the users need to decide if it is a HC then clicking "Yes" or "No" button. If the users make a mistake, a prompt message will give detailed explanations.

The practice activities provide users with open questions to give them the chances to strengthen their memory of the knowledge they just learnt. Activity 1C (*Similar or different*) lets users compare pairs of similar HCs to raise users' awareness that HCs may be re-worded in the real-life use. It provides HC pairs and the users needs to judge their similarities by dragging a slider bar.

Activity 2 (*What would you buy?*) implies the users to check the HCs in their real shopping activities. It provides a shopping scenario simulation that users decide which item they would like to buy. First, a user needs to select one out of four products to put into the shopping basket, then, six versions of the selected product are given. All the products are distinguished with HCs. The users can choose only one (or zero) item to buy based on their preference.

In Activity 3 (*Design your own food pack*), users can design their own food pack as well as their own HCs. First, users need to choose one product (i.e. milk, yoghurt, etc.), then designing a HC for the product. The designing process is governed by a template (Figure 5). It covers a group of words which are sufficient to write usual HCs for the option products. Based on the template, users only need to literally select the words for the HC sentences they are creating. The template always lead users to create legal HCs, and the results are passed to the manufacturer platform. Finally, this activity also gives users the chance to manually design the product package by changing the icon, colour, and layout.

4 MANUFACTURER PLATFORM IMPLEMENTATION

The manufacturer platform contains NLP-based models which support manufacturers to evaluate consumer preferences of HCs automatically, without the need of conducting user surveys. It simulates the results of the offline consumer surveys that to what degrees that consumers are attracted by the HCs. For the given HCs, the manufacturer platform can show the *general consumer preference scores* for the population, and the *target consumer preference scores* for groups of consumers. In the platform, consumers are grouped by their characteristics (e.g. age-based groups, gender-based groups etc.), and the platform can show the preference scores for the groups of a single characteristic or the combination of multiple characteristics.

The interface of the manufacturer platform (Figure 6) allows users to input query HCs. Users can choose the target consumer groups of characteristics on the sidebar. Then, the interface shows the analysis of the query HCs. It suggests different wordings of the query HC, but has the same nutrition and health benefits. The predicted consumer preference scores of the suggested HCs are shown to the users, which helps users to make decisions. Figure 6 show the example case that the specified target characteristic is "age between 25-34", so the *target consumer preference scores* are only for the consumers within this age range. Users also can select multiple characteristics for example both "age between 25-34" and "Female".

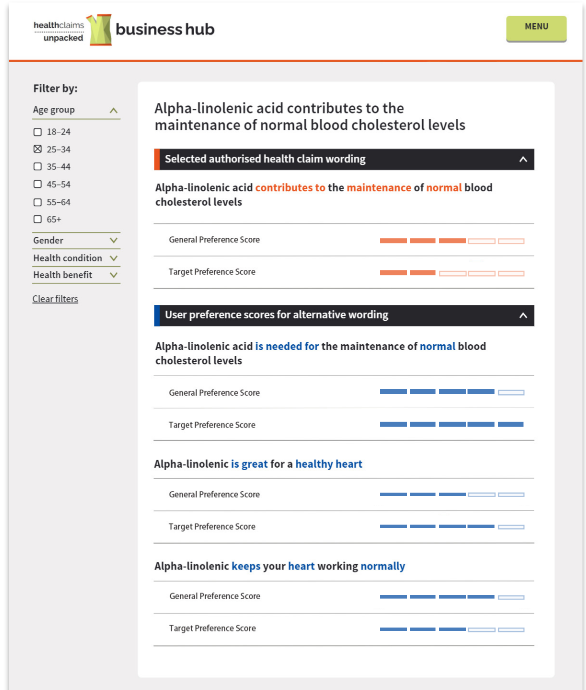

Figure 6: The interface of the Manufacturer platform

Since the consumers in different groups may have different cultures and personal preferences [2], food manufacturers usually only focus on few target consumer groups whom their products sell to.

The consumer preference scores are calculated through a two-step process. First, the *general consumer preference scores* are calculated base on a pre-processed statistic of a large scale offline consumer preference survey; then, the *target consumer preference scores* are calculated based on the *general consumer preference scores* as well as the knowledge of the differences between each consumer group (i.e. the data from Activity 3).

4.1 Predicting General Consumer Preference

To predict the *general consumer preferences*, we conduct a scenario experiment, asking subjects to help a virtual friend to choose the food products as gifts. In each task, two approved HCs are randomly displayed representing the two gifts. For the current version of the demo system, the scenario experiment uses 601 publicly available HCs for the nutrition of vitamins and minerals. They are the major nutrition for food products appeared in EU supermarkets. We finally recruited 200 subjects and collected 3600 answers (i.e. 3600 tasks).

Then, a neural network model is trained to predict the *general consumer preference scores* based on the experiment results. The model is mainly a 20-layer Transformer model [8], whose input is a HC sentence with a [sos] token attached to the front of the sentence. The output is a preference score. There is a feedforward network following the transformer layers, and the output vector for the [sos] token of the last layer transformer is fed in the feedforward network. The output of the feedforward is a real number, which is used as the preference score.

Since the scenario experiment results are the paired HCs with labels denoting the preferred one of each pair, the prediction model is trained by adopting the Learning-to-Rank strategy [3]. In the training process, the model predicts the preference scores for each HC in a pair individually, and the optimiser updates the model according to the distance between the two scores. This training strategy aims to ensure that the preferred HC gets a higher score than the non-preferred HC as much as possible.

Since the strategy of Learning-to-Rank does not limit the value range of the preference scores (i.e. after training, we cannot have the max and the min scores for HCs), we calibrate the scores among all the publicly available HCs. Specifically, we score and rank these HCs by the trained model, then, split them into n intervals such that each interval contains the same number of HCs. Thus, the preference scores can be transferred into a n-point scale score, which is denoted by the cardinal number of the intervals. When a preference score falls in the value range of an interval, we use the cardinal number of the interval to represent the absolute levels of the consumer preference to the HC.

4.2 Predicting Target Consumer Preferences

Based on the *general consumer preferences*, we calculate the biases for each consumer characteristic to estimate the *target consumer preferences*. We hypotheses that consumers are attracted by the HCs the consumers create. So, a regression model is adopted which learn from the results of Activity 3 for estimating the biases. The input of the model is the created heath claims (e.g. words and punctuation), which are regarded as word-bags; the output is the characteristic indicating what consumers are more likely to create this HC in terms of the characteristics.

Both the HC word-bag and the consumer characteristics are represented by vectors (denoted by $\mathbf{w}$ and $\mathbf{c}$ respectively), and the model is to learn a matrix ($\hat{\mathbf{M}}$) to project $\mathbf{w}$ to $\mathbf{c}$ through a linear regression process. Specifically, we use least squares to obtain $\mathbf{M}$. All the constructed HC and the corresponding characteristics of the creators are transferred into one-hot vectors, and the vectors are stacked as two matrices – the word-bag matrix ($\mathbf{W}$) and the characteristic matrix ($\mathbf{C}$). According to least squares, $\hat{\mathbf{M}}$ can be found by Eq. 1.

$$\hat{\mathbf{M}} = (\mathbf{W}^T\mathbf{W})^{-1}\mathbf{W}^T\mathbf{C} \tag{1}$$

Then, given an arbitrary heath claim $\mathbf{w}'$, we can calculate the corresponding $\mathbf{c}'$ by Eq. 2.

$$\mathbf{c}' = \mathbf{w}'\hat{\mathbf{M}} \tag{2}$$

The values in $\mathbf{c}'$ are the biases indicating what consumer characteristics lead to the use of the corresponding HC. It denotes the relationship preferences between the population and each characteristic-based group. Given the numbers of consumers that each characteristic involves (denoted by p_i where i denotes the dimension number of c', and p denotes the sum of every p_i), we can also calculate a preference score for the population ($\tilde{u}$) according to c' by Eq. 3.

$$\tilde{u} = \sum_i \frac{p_i}{p} c'_i \tag{3}$$

Note that, $\tilde{u}$ **cannot** be used as a *general consumer preference score* (like in § 4.1), because $\tilde{u}$ do not reflect the overall preference of the population. Considering the *ordinary case*: if there were only one considerable characteristic for consumers and all the consumers had the characteristic, $\mathbf{C}$ would have only one column (all the entries would be 1), so that $\mathbf{c}'$ would always be a constant number.

To obtain the estimations for preference scores for the consumer characteristics, the platform introduces a calibration parameter λ to calibrate $\tilde{u}$ and the values in c' according to the (n-scaled) *general consumer preference score* in § 4.1 (denoted by u introduced). The calibration is processed by Eq. 4.

$$u = \lambda\tilde{c}' = \sum_i \frac{p_i}{p} \lambda c'_i \tag{4}$$

When we have u and c', we can find λ. When we have the λ, we use the entries of $\lambda c'$ to denoted the preference prediction for each consumer group (i.e. Eq. 5). In our system, u_i is also rounded to the nearest integer.

$$u_i = \lambda c'_i \tag{5}$$

We evaluated the accuracy of this method, by randomly split the dataset into training and testing sets. The testing set roughly consists of 10% data records. The average accuracy is 0.82 based on the 10-cross-validation.

The model to predict the consumer group based preference scores is updated at run-time. Since the least squares is quick enough, when the consumer platform receives new consumer responses, the model updates the values of $\hat{M}$ and each p_i. Therefore, when the platform accumulates the consumer responses, the model performance of the prediction will be enhanced.

5 CONCLUSION

The digital toolkit released its English version in November 2019, and the other versions (French, German, and Polish) in the summer of 2021. The toolkit has already significantly contributed to our knowledge of the linguistic determinants of consumer understanding of HCs. Although the manufacturer platform is in the last stage for the launch to all the manufacturer, a large number of feedbacks from manufacturers show great interest in it with positive comments on the demo.

By February 2021, a total of 1067 HCs were co-created by users of the toolkit. Many of these claims significantly diverged from the EFSA-approved versions, but users often showed consensus in the kinds of wordings they preferred. While previous research has shown that consumers prefer more concise and simple wordings for HCs, our project has highlighted the specific kinds of linguistic strategies that consumers prefer; for example, in many of the co-created claims consumers replaced the lengthy noun phrase characteristic of EFSA approved claims (e.g. "the maintenance of") with shorter verb-phrases (e.g. "maintains"), and consumers also favoured claims with more personal language (for example, using the words "you" and "your"). Insights such as these provide an important resource for regulators, enforcement bodies, and, most of all, manufacturers for communicating HCs more effectively.

6 ACKNOWLEDGEMENTS

This project is funded by European Institute of Innovation and Technology (EIT) Food/EU Horizon 2020 (project number 19098). The authors would like to thank the funder EIT food and the great help and support of other team members of the project.

REFERENCES

[1] Azzurra Annunziata and Angela Mariani. 2019. Do consumers care about nutrition and health claims? Some evidence from Italy. *Nutrients* 11, 11 (2019), 2735.

[2] Ross Brennan, Barbara Czarnecka, Stephan Dahl, Lynne Eagle, and Olga Mourouti. 2008. Regulation of nutrition and health claims in advertising. *Journal of advertising research* 48, 1 (2008), 57–70.

[3] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *Proceedings of the 24th international conference on Machine learning*. 129–136.

[4] Liisa Lähteenmäki. 2013. Claiming health in food products. *Food Quality and Preference* 27, 2 (2013), 196–201. https://doi.org/10.1016/j.foodqual.2012.03.006 Ninth Pangborn Sensory Science Symposium.

[5] Giuseppe Nocella and Orla Kennedy. 2012. Food health claims–What consumers understand. *Food Policy* 37, 5 (2012), 571–580.

[6] Jacob L Orquin and Joachim Scholderer. 2015. Consumer judgments of explicit and implied health claims on foods: Misguided but not misled. *Food policy* 51 (2015), 144–157.

[7] A. Saba, M. Vassallo, R. Shepherd, P. Lampila, A. Arvola, M. Dean, M. Winkelmann, E. Claupein, and L. Lähteenmäki. 2010. Country-wise differences in perception of health-related messages in cereal-based food products. *Food Quality and Preference* 21, 4 (2010), 385–393. https://doi.org/10.1016/j.foodqual.2009.09.007

[8] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*. 5998–6008.

[9] Brian Wansink, Steven T Sonka, and Clare M Hasler. 2004. Front-label health claims: when less is more. *Food Policy* 29, 6 (2004), 659–667.