

Towards Tailoring Digital Food Labels: Insights of a Smart-RCT on User-specific Interpretation of Food Composition Data

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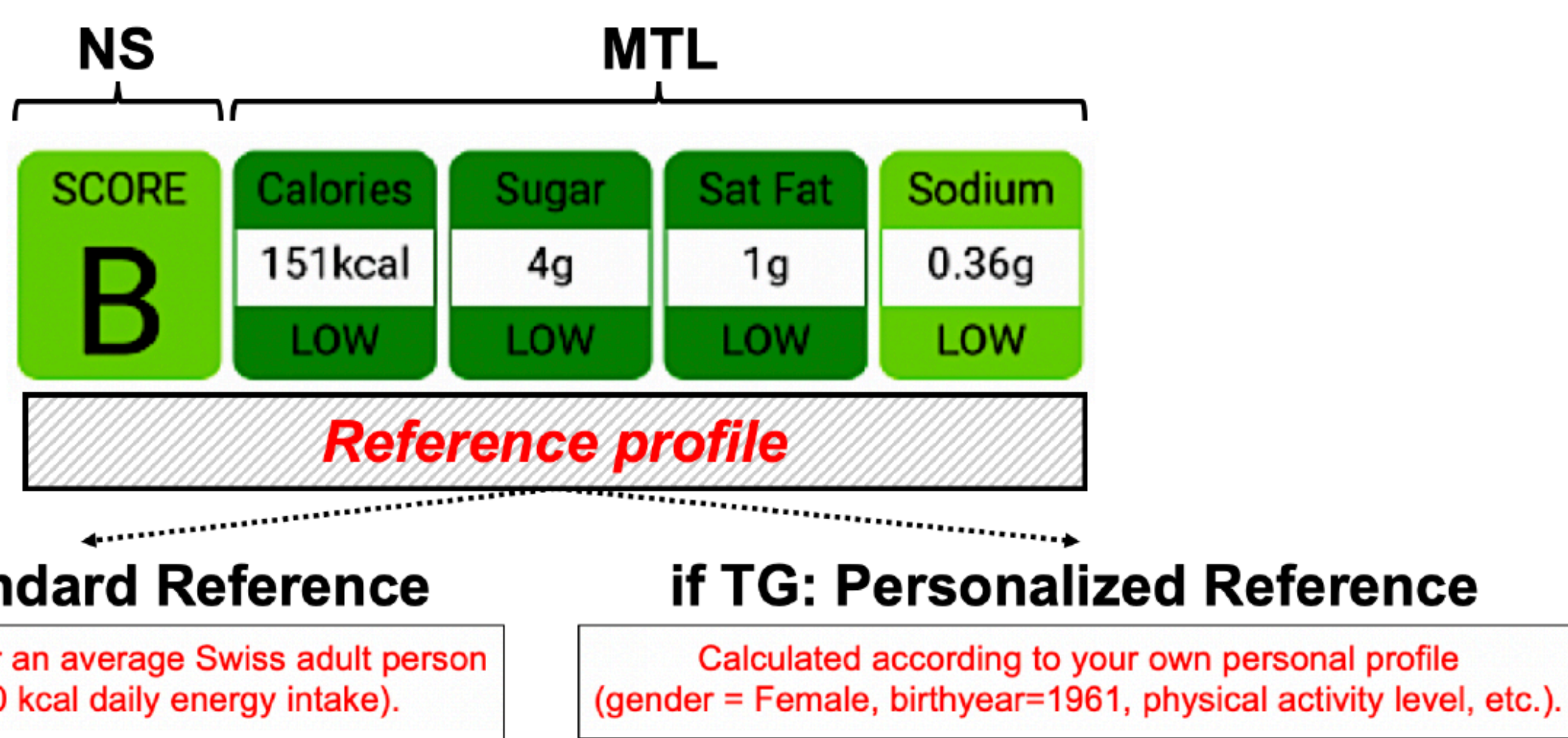


1 Motivation

This study extends the growing stream of diet-related mHealth research that examines diet outcomes in relation to food purchasing behavior via barcode scanning [1], [2], [3], [4] which so far have neglected the role of tailoring user-specific needs within the application [2]. Indeed, labels are criticized for giving standardized recommendations that overlook individual needs. To assess the potential of consumer-specific tailored labels, we thus developed and tested a tailoring logic for adapting labels to individual dietary requirements and a smartphone app that then provided tailored food labels after scanning a product's barcode.

2 Research Model

The tailoring logic was developed with dietitians, accounting for gender, age, activity, preferences, diet-related diseases. The label showed a combination of established labelling systems: Nutri-Score, which caters more towards illiterate users, and Multiple Traffic Light, which caters more towards literate users, e.g. who are familiar with nutrients, daily intake levels and impact of dietary behavior.



3 Experiment Design

The app was published for iOS & Android in four languages. During setup, users are randomly assigned to two groups. In an initial survey, they enter data about diet-related diseases, body mass index (BMI), physical activity level (PAL), etc. During the study, the app shows either a tailored or standardized label, logs activity and collects motivational data in a final survey.

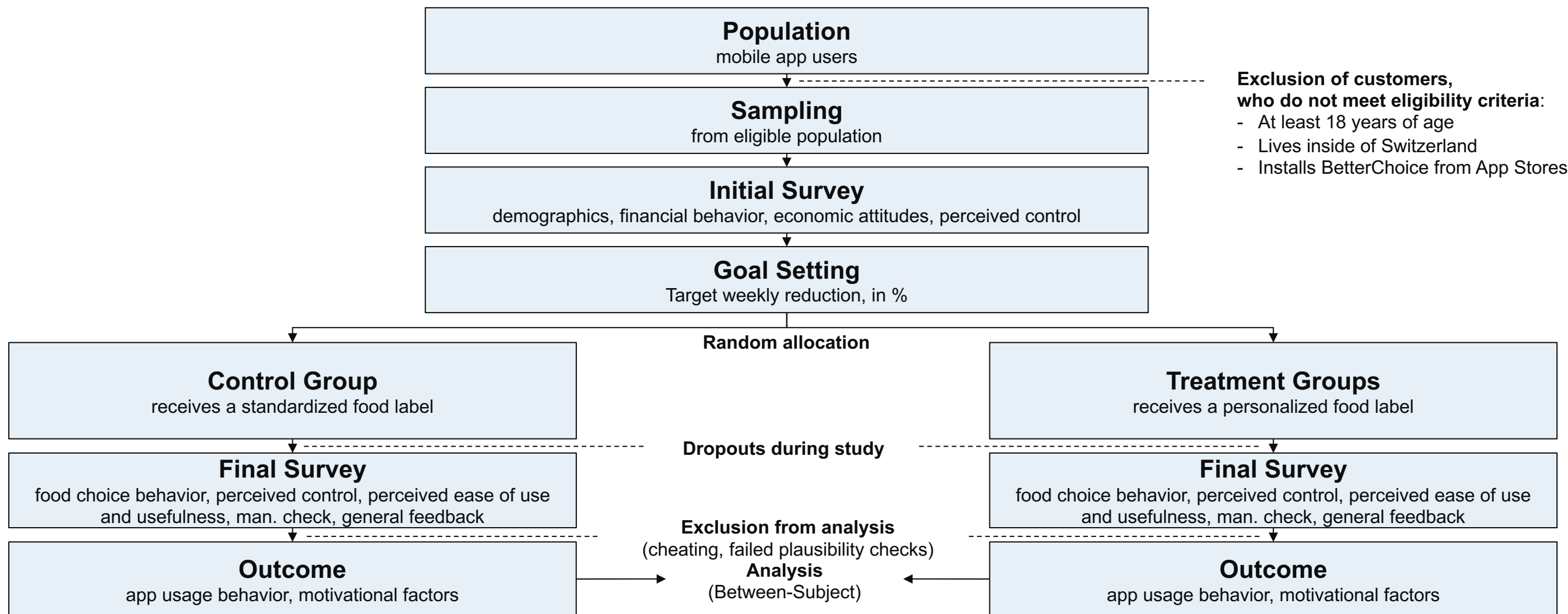


Fig. 2. Experiment design following the Smart Randomized Controlled Trial approach, encoded within BetterChoice app

4 Mobile App & Field Study

Participants receive condition-dependent feedback, based on the experiment design. Together with the Swiss Society for Nutrition (SGE-SSN), a tailoring framework was developed adjusting food labels towards individual app users. Depicted below, an example of a 1961-born female with low physical activity (PA) and a 1992-born male with high PA is shown. The tailoring framework is based on dietary needs (table 1) and on diet-related diseases, for which the food label was also tailored to.

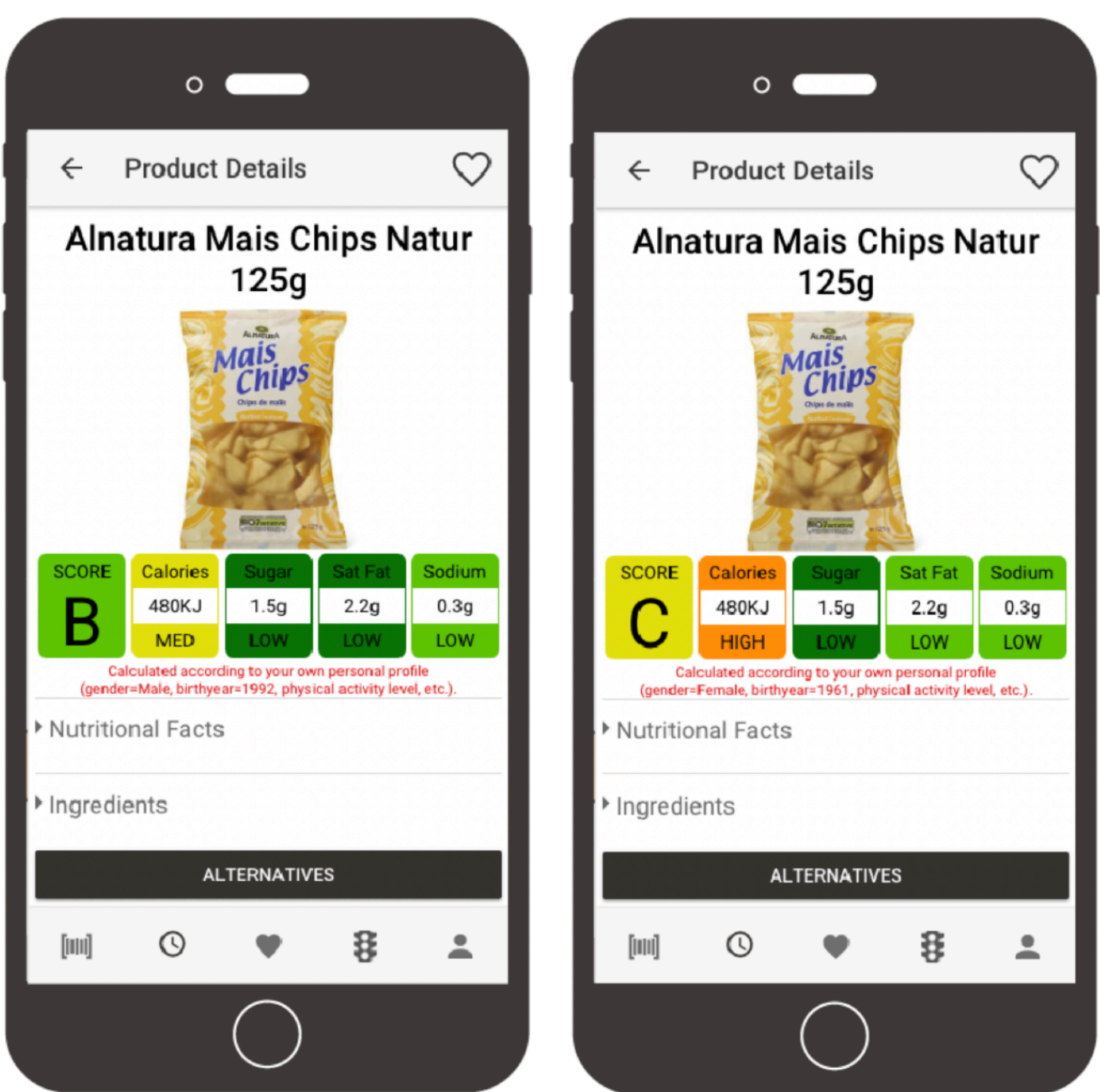


Table 1: Tailoring of Digital Food Label				
	Energy	Sat Fat	Sugar	Salt
Gender				
Male	+12.5%	+12.5%	+12.5%	-
Female	-12.5%	-12.5%	-12.5%	-
Other	-	-	-	-
Age				
18-44	-	-	-	-
45-65	-10.0%	-10.0%	-10.0%	-
over 65	-20.0%	-20.0%	-20.0%	-
PAL				
1.4	-16.0%	-16.0%	-16.0%	-16.0%
1.5	-12.0%	-12.0%	-12.0%	-12.0%
1.6	-8.0%	-8.0%	-8.0%	-8.0%
1.7	-4.0%	-4.0%	-4.0%	-4.0%
1.8	-	-	-	-
1.9	+4.0%	+4.0%	+4.0%	+4.0%
2.0	+8.0%	+8.0%	+8.0%	+8.0%
2.1	+12.0%	+12.0%	+12.0%	+12.0%
2.2	+16.0%	+16.0%	+16.0%	+16.0%
2.3	+20.0%	+20.0%	+20.0%	+20.0%
BMI				
<18.5	+15.0%	+15.0%	+15.0%	-
18.5-25	-	-	-	-
25-30	-5.0%	-5.0%	-5.0%	-
>30	-10.0%	-10.0%	-10.0%	-

Legend: Energy (kJ), Saturated Fat (g), Sugar (g), Salt (g), all per 100g of product, PAL = Physical Activity Level

5 Status Quo

The application followed a smart-RCT design, randomly attributing users with tailored or standardized labels.

27 users met the eligibility criteria for our study. We found promising evidence that tailored digital food labels are perceived as more helpful, relevant, and recommendable than especially in the absence of FoPL. We plan to publish the study findings, when over 50 users have completed the study protocol (i.e. use the app on at least 4 different days and complete the final survey).

Table 4. Self-Reported Technology Acceptance (N=27)			
Construct	TG mean (SD)	CG mean (SD)	P-value
Intention to Use	4.39 (0.63)	3.77 (0.96)	.15
1.1: I intend to keep using the app during my next shopping trips over the next weeks.	4.09 (0.67)	3.50 (0.87)	.088 ^A
1.2: I will recommend the app to my friends, because I think they should try it out.	4.72 (0.46)	3.81 (1.07)	.028*
1.3: I have a very positive opinion/perception about the app.	4.36 (0.77)	4.00 (0.94)	.34
Performance Expectancy	3.90 (0.94)	3.22 (0.93)	.13
2.1 This app supports me in my struggle to identify healthy products among the many products available today.	3.82 (1.03)	3.43 (0.79)	.34
2.2 This app helps me in assessing my dietary intake from my grocery purchases.	4.27 (0.96)	3.31 (0.91)	.026*
2.3 This app gives me recommendations that are very relevant to my personal lifestyle.	4.18 (0.83)	3.25 (1.09)	.033*

*: significant on $P < .05$, ^A: significant on $P < .1$
Agreement Likert scale for all items [1=very low ; 5=very high]

6 References

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