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TOWARDS A DIGITAL NATIVE ERA IN NUTRITION: INTRODUCING THE M-FORMAT LABELING

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Abstract. The advent of m-commerce has reinvented and simplified the shopping experience for the digital native generation. The following questions were the starting points for this research: is nutrition labeling important in purchase decisions? Could a new format for food nutrition labeling in m-commerce be the optimal way to inform the younger generation and enrich their shopping experience? This study continues the authors' research on the food preferences of the younger generation by conducting a quantitative study on a sample of 364 students. The aim of the paper is to identify the factors that influence online food orders and the ways in which nutrition labeling can enhance consumers' purchasing experiences and eating habits. The results show that nutrition facts play an important role in online purchases of new or unfamiliar foods. Control over one's own diet and a higher income also make digital natives more interested in ordering food online. The use of a mobile format for nutrition labeling would be the necessary update for the food industry to turn nutrition data into added value, help consumers get a balanced diet and personalize nutritional needs, and for policymakers to adjust nutrition standards and policies toward healthier and more responsible consumption patterns.

Keywords: consumer behavior, food, digital natives, mobile commerce, m-format, nutrition labeling, logistic regression.

JEL Classification: D11, L66, L81, M21.

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1. Introduction

Convenience (e.g., ease of use) and hedonistic motivations have the greatest impact on consumer purchase response (Monge, 2021), along with an increase in e-commerce due to COVID-19 lockdown. The rise of mobile apps has led companies to embrace m-commerce apps as a complementary business channel and a way to revolutionize the shopping experience (Ngubelanga & Duffett, 2021). Unfortunately, the relationship between m-commerce food purchasing behaviors and attitudes toward nutrition labels remains under-investigated. Our research identified papers connecting either the topics of nutrition labeling and eating behavior (Roodenburg, 2017; Jones et al., 2019; Medina-Molina et al., 2020; Ikonen et al., 2020; Hernandez-Fernandez et al., 2022) or mobile technology and eating behavior (Maity & Dass, 2014; Kapoor & Vij, 2018; Akram et al., 2020; McLean et al., 2020; Mauch et al., 2021) and rarely a direct link between nutrition labeling and consumer choice in the online environment (Stones, 2016; Zou & Liu, 2019; Brewer & Sebby, 2021; Dana et al., 2021). In the continuously expanding mobile-oriented society the use of smartphones and other mobile devices became the favored method for accessing a wide range of information (Nowlan, 2013). Within this particular framework, this research proposes the introduction of "m-format nutrition labeling" – being the translation of nutrition information into a digital format so that it is mobile-ready, designed in a visual format, user-friendly, easy to understand, and allows information to be shared with other applications.

This paper aims to determine the influence of nutrition labeling and other relevant factors such as income level, gender, responsibility for setting one's own menu and use of mobile devices on online food purchases of young consumers. Taking into account the generation of digital natives with a specific psychological profile, the paper explores how to improve the online shopping experience for food products. The present research builds on a previous study on the informative role of nutrition labeling in guiding students' eating behavior. Thus, the directions, objectives, and hypotheses for the present quantitative research are identified using an inductive-deductive reasoning in a focus group based on an interview guide with a structured approach (Bobe et al., 2019). The paper is divided into three sections that address: (1) a brief literature review providing theoretical context on the imperative of adapting nutrition labeling to digital native behavior, (2) the materials and methods used to conduct the research, including hypotheses and the use of logistic regression, (3) results and discussions on the binary logistic regression model and hypothesis testing interpreted followed by conclusions.

2. Literature review

2.1. Food m-commerce – the new normality

Demand, food supply, and purchasing patterns were significantly affected by the COVID-19 disruption (EIT Food & SATEAN, 2021). Before the COVID-19 pandemic, food m-commerce had a slower evolution than in other online sectors. Although initially, the lockdown was the engine of online sales growth for food products, the upward trend was sustained by retailers' efforts to retain customers and preserve their purchasing behavior (Cioba, 2020). Digitalization in food delivery has intensified (Naveena & Mathan Kumar, 2021), making it easier to buy food and reshaping existing markets (Dsouza Prima & Parappagoudar, 2021). The growing share of Millennials and Generation Z in the population structure as digital native generations, increased access to the Internet and mobile devices, and the speed and convenience of digital commerce (Verhoef et al., 2015) have led to increased interest in online shopping. At European level, young people aged 16–24 were the largest group of online shoppers in 2019, dethroning the 25–54 age group (Radu, 2021). In Europe, online food trade accounted for 5% of the market in 2020 (McKinsey, 2020), and 6.9% of the market in 2021, and forecasts indicate that it will double its share by 2030, as digital natives become the predominant buyers, according to PwC Romania (ZF, 2022). After COVID-19, the development of digital sales channels has accelerated and the strategic focus has shifted to food supply, promoting the emergence of new forms of integrated supply and marketing (Wang et al., 2023). New innovative forms of digital commerce have become a popular choice for online shopping among young consumers due to their attractive graphics, pragmatic communication and interactive experience. In the digital age, weighing the interaction of the influence of social media and e-commerce platforms on consumer behavior and food choice can optimize the focus of nutrition labeling strategies on the individual needs of the consumer (Priya & Alur, 2023).

2.2. Adapting nutrition labeling to current consumer behavior

Nutrition labeling is a communication tool to change consumer behavior (European Commision, 2020), which takes into account behavioral determinants related to motivation, knowledge, trust, preferences, and choices (Andrien & Food and Agriculture Organization of the United Nations, 1994). In addition, nutrition labeling is an important policy goal to help consumers make healthier food choices (Kanter et al., 2018). The effectiveness of nutrition labeling in successfully changing purchasing behavior depends on a number of conditions: it must be attractive, accepted, and understandable in order to influence food choices and, implicitly, health (Grunert & Wills, 2007). Before the COVID-19 pandemic, although different ways of interpreting nutrition labeling (e.g., Nutri-Score) do not moderate the relationship between perceived health and purchase intention (Medina-Molina & Pérez-González, 2020), this has produced useful results showing the positive evolution of awareness and use of this type of labeling (Sarda et al., 2020). Food manufacturers should be aware of the need to improve attitudes toward the product through labeling and nutritional information to increase credibility and purchase intention (Hernandez-Fernandez et al., 2022). Applications have been developed to allow consumers to retrieve nutritional information based on barcode scanning and interpretive front-of-pack labeling methods (Silva et al., 2022). Such apps that support healthy food delivery could be further developed by introducing nutrition labeling (Mauch et al., 2021). As online meal ordering is an increasingly common practice, it is important to encourage people to make healthy food choices (Dana et al., 2021). The evidence for linking nutrition labels with interactive digital interventions such as shopping cart feedback is encouraging and shows that more intrusive interventions are needed to increase their effects on healthy food choices and consumer's health level (Schruff-Lim et al., 2023). In the post-pandemic period, scientific interest continued towards better adapting the nutrition label to the specific needs of the consumer for a balanced food consumption, creating the premises for a sustainable eating behavior. Considering that mobile smart devices are used not only for information but also to complete purchases, food policy should adapt to the young digital natives who are sensitive to pragmatic and age-appropriate forms of communication and technology savvy.

2.3. The digital native and the app-generation consumer

Digital natives are defined as people who have lived their entire lives using and being surrounded by modern digital technology in all areas of their lives (Prensky, 2001). To define them, the Digital Native Rating Scale is used, grouping their characteristics under four factors: They have grown up with technology, they are comfortable multitasking, they rely on graphics for communication, and they enjoy instant gratification and reward (Teo, 2013). When students were tested on this scale (Akçayır et al., 2016), results showed that gender and academic disciplines did not affect digital natives' self-perceptions, but geographic differences in where they grew up and had more experience with technology did. It is worth considering whether digital native buyers are hedonistic consumers seeking to fulfill their desires or utilitarian consumers seeking to fulfill their needs in practical ways (Ashraf et al., 2021). Younger mobile app users, unlike older generations, value convenience over ease of use (Gurtner et al., 2014). They are used to accessing the information and benefiting from the apps anytime and anywhere, and they are also more tech-savvy, overcoming any difficulties and adapting to using different devices and apps. Criticisms have been raised regarding transparency and privacy, accuracy and objectivity of information, negative social influence on consumer diet, and lack of inclusion of relevant senses other than sight in the food experience (Jacobsen et al., 2021). Integrating nutritional information into the m-commerce environment would enable connections to other mobile apps in the health, nutrition, and lifestyle categories (Figure 1).

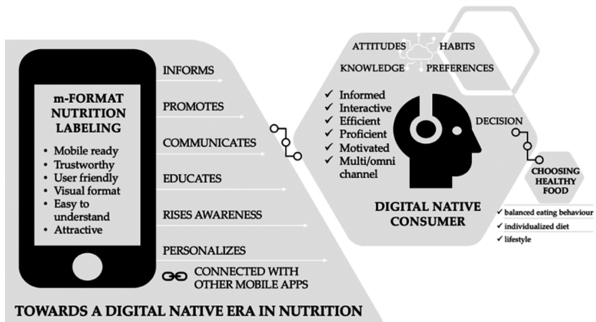

Figure 1. Bringing nutrition into the digital era with the m-format nutrition labeling (source: own representation)

Nutrition labeling allows digital natives to examine, select, and compare foods, which would be easier and more effective in m-commerce with such apps. For this reason, traditional nutrition labeling needs to be rethought and translated into a m-format to become mobile-ready: more visible (visual format), designed from the very beginning to be accessible in a expressive format with less emphasis on text, user-friendly, and most importantly, easy to understand to convey its content without errors. Translating data into suggestive graphical representations is useful for effective, trustworthy, and attractive communication, because simply stating the energy value (expressed in kilocalories or kilojoules) and the amounts of substances with energetic and biological role (in grams or milligrams) is not sufficient. This makes it possible to determine the daily requirement of energy and essential nutrients at the individual level, depending on age, sex and physical activity.

3. Materials and methods

Qualitative research (Bobe et al., 2019) has shown how nutrition labeling influences young consumers' eating habits. Based on the exploratory descriptive objectives and data collected, the following elements influenced this consumer segment's food purchasing decision and formed the basis for this study: (1) most consumers need to know the nutritional profile of the foods they purchase to size daily portions, but nutrition facts can confuse and mislead untrained consumers; (2) nutrition labeling does not have a decisive impact on consumption decisions, but it does improve consumers' perception of the nutritional profile of foods and can lead them towards healthier options; (3) women pay more attention to their diets and to the fat and sugar content of the products they eat; (4) to correct unbalanced dietary behaviors, nutrition education of the population and information delivery must be improved.

These findings, linked to other relevant studies on:

- changes in food purchasing behavior (Ashraf et al., 2021; Monge, 2021);
- the expansion of mobile food commerce (Dana et al., 2021; Zou & Liu, 2019);
- the digitization of food retailing (Dsouza Prima & Parappagoudar, 2021; Fernandez & Raine, 2021; Naveena & Mathan Kumar, 2021);
- the use of mobile smart devices as a ubiquitous part of shopping (Gurtner et al., 2014; Verhoef et al., 2015; Mauch et al., 2021);
- the impact of nutrition labeling on consumer behavior and offline/online purchasing decisions (Stones, 2016; Zou et al., 2019; Ikonen et al., 2020);
- the growing share of digital native consumers (Prensky, 2001; Thinyane, 2010).
- led to the development of the following hypotheses:
  - H1a: Nutrition labeling significantly and positively influences online food purchases.
  - H1b: Interest in nutrition labeling for new/unfamiliar products has a significant and negative impact on online food purchases.
  - H1c: Interest in nutritional labeling for familiar products significantly and directly (positively) influences online food purchases.
  - H2: A higher income level has a significant and direct (positive) influence on the decision to order food online.
  - H3: Women are more hesitant to order online because they lack adequate nutrition labeling.
  - H4: Responsibility for setting one's own menu has a significant and direct (positive) impact on online food ordering choices.
  - H5: Adapting the nutrition labeling for mobile devices (m-format) is a crucial step in meeting the expectations of digital native consumers and improving their overall shopping experience.

The study investigates the factors influencing food consumption. Data used for analysis were obtained following the application of an exploratory research, through an online questionnaire, between April 2021 and April 2022, on a random sample of 364 students from the Faculty of Business and Tourism within the Bucharest University of Economic Studies. After data validation, 350 respondents aged 18–24 years remained in the sample, of which 113 were male (32.3%) and 237 were female (67.7%). The difficulty of conducting research on consumer behavior determined by the use of nutritional labels on a representative random sample led to the inclusion of people in the sample according to the criterion of relevance (Jurconi et al., 2022). The questionnaire used in the present study includes 24 questions aimed at identifying new food consumption habits and long-term food trends, with the last 5 questions outlining the socio-demographic profile of the respondents. Outlier responses from respondents who reported a daily energy requirement of less than 500 kilocalories (3 respondents) or were aged 25–44 years old (11 respondents) were excluded from the analysis. Thus, the final sample for data analysis included 350 students aged between 18 and 24. In terms of identifying variables (Table 1), the study respondents were categorized by age, gender and income.

Correlation and regression analyzes are used to identify factors influencing food purchasing behavior among the younger generation included in the analysis. Individual behavioral models are constructed using qualitative variable analysis methods such as the McFadden logit model (McFadden, 1968). Logistic regression, or the logit model, measures the

Table 1. Distribution of respondents by age, gender, level, source and average income

Age (in years):	Female	Male	Source of income			Average income (monthly, EUR)
18	7	–	only parental financial support	both own income and parental financial support	only own income	400–600
19	64	29				
20	42	19				
21	100	48				
22	20	11				
23	2	5				
24	2	1				
	237	113	162	147	41	350
Grand Total	350		350			350

relationship between dependent categorical variables and one or more independent variables that are generally, but not necessarily, continuous by estimating event probabilities corresponding to the categorical variables (Hurlin, 2015). Logistic regression is a special case of generalized linear models and thus an analogous case of linear regression (Anderson et al., 2017; Manea et al., 2016; Popa, 2010). Dichotomous logit models have as explanatory variable the probability of occurrence of an event depending on exogenous variables. At the same time, understanding odds and odds ratios helps to properly evaluate a logistic model. In this study, the logistic function had as an endogenous variable the respondents' preference to consume a certain type of food (ordered online/prepared at home), and the objective is to identify the factors that influence the type of food purchase. The predictive variables are presented below:

Model 1: Menu decision (In2), Income level (In22) and Gender (In23)

The current study examines the relationship between daily menu choice, income level and gender in online food ordering and the use of digital nutrition labeling. Previous research suggests that daily food choices significantly influence consumer behavior related to the use of nutrition labels, such as menu presentation or the organization of daily food choices that significantly influence food consumption preferences (Fernandes et al., 2016; Roberto et al., 2010; Vanderlee & Hammond, 2014). In addition, individuals who actively make daily food choices are more receptive to digital nutritional information, as they have greater control over their food choices. On the other hand, delegated menu planning may favor online ordering services to simplify the food selection process. Recent studies have examined the impact of front-of-pack nutritional information on consumer decisions (Roberto et al., 2021), analyzed the effectiveness of mobile applications in improving food choice (Turner-McGrievy et al., 2017), and investigated the influence of nutritional information systems on food preferences (Cecchini & Warin, 2016). These studies support the hypothesis that easy access to digital nutritional information positively influences consumers food choices, an opportunity for deeper consumer understanding, promoting healthier choices and a more responsible approach to food purchasing. In this sense, Hobin et al. (2016) found that by providing more nutritional information significantly reduces parents' risk of choosing unhealthy food options. The financial factor, represented by income level, is another crucial aspect of this equation. Higher income individuals may be more inclined to use digital technologies, invest in properly labeled foods and rely on online ordering to save time. Nguyen and Powell (2014) showed that high-income adults consume less energy, while middle-income men and low-income women have the highest energy intake. Recent studies also suggest that women are more likely to pay attention to nutritional information and to use digital labels to make informed food choices, especially concerning health and the quality of consumed products (Oostenbach et al., 2019). On the other hand, Ali et al. (2021) discovered gender differences in online food ordering intentions, with optimism and innovation positively influencing men while insecurity and discomfort are more pronounced among women. Furthermore, men more frequently possess advanced technological skills, and more enthusiastic about adopting new gadgets compared with women (Ali et al., 2021; Elliott & Hall, 2005; Gutek & Bikson, 1985; Harrison & Rainer, 1992; Tsikriktsis, 2004).

Model 2: Frequency of reading nutrition label for new / unfamiliar products (In13.1), Frequency of reading nutrition label for familiar products (In13.2)

The introduction of these two variables adds an extra dimension to the analysis of the interactions between reading nutrition labels, food choice and online food ordering. Individuals who pay attention to nutrition labels for new or unfamiliar products are more likely to use digital nutrition labeling to make informed dietary choices. This proactive approach to understanding and evaluating the nutritional content of products may be linked to online ordering services for quick and clear access to information. The use of nutritional information is particularly important in certain contexts, e.g. when comparing the nutritional content of two products or when buying a product for the first time. Young women, particularly those with children and higher education show increased interest in specific sugar content (Anastasiou et al., 2019; Gomes et al., 2017; Prada et al., 2021).

Annunziata and Vecchio (2012) stated that 48% of people pay attention to food labels when buying a new product, while only 4.3% routinely read them. A more detailed perspective is provided by Mediratta and Mathur (2023), who showed that 76% of higher income adults read nutrition labels, but few can understand all the information correctly. All of these findings suggest that consistent attention to nutrition labels may lead to more use of digital nutrition labeling and online ordering services to make informed food choices and confirm already existent information, regardless of familiarity with the product.

Model 3: The influence of nutrition labels on consumption decisions (In12)

The introduction of a new complete predictor variable complements the analysis of consumer behavior, its interaction with digital nutritional labeling, and online ordering of food products. The authors suggest that individuals who place great importance on nutritional labels may be more interested in using digital nutritional labeling. Therefore, these individuals might be more inclined to use digital nutritional labels to obtain clear and relevant information before making food choices. In addition, these consumers might also turn to online ordering services, seeking precise and quick information. Concern for nutritional labels could influence their use of online food ordering, preferring products that are well-labeled and provide the necessary nutritional information. Tandon et al. (2011) argue that while food labeling can increase consumer awareness, it doesn’t necessarily reduce calorie consumption. Annunziata and Vecchio (2012) elaborate on this, highlighting that some consumers maintain their purchasing habits despite nutritional labeling, while others (e.g. with healthy eating habits) rely on it to inform and change their purchasing decisions, positively influencing their dietary habits.

4. Results and discussion

Table 2 shows that half of the respondents are sedentary or have reduced physical activity (light movement 1–3 days / week), a situation that can be attributed, in part, to the changes in daily routine after the pandemic. It is worth noting that 59 of the 350 respondents did not know the value of their reference daily intake (RDI). This shows that 16.85% of digital natives are not concerned about food intake. Also noteworthy is the perception and awareness of high calorie consumption among 16% of respondents who are predominantly sedentary or have low physical activity.

Table 2. Distribution of respondents by daily caloric intake, physical activity, and RDI

Lifestyle / daily energy requirements (in kilocalories):	hypo-caloric (<RDI*)	normo-caloric (=RDI)	hyper-caloric (>RDI)	Total
sedentary (very little or no movement)	13	18	8	39
500–1500 kcal	5	5	–	10
1500–3000 kcal	3	9	6	18
I do not know	5	4	2	11
reduced activity (easy movement 1–3 d/w**)	23	94	19	136
500–1500 kcal	16	19	4	39
1500–3000 kcal	4	56	8	68
I do not know	3	19	7	29
moderate activity (moderate intensity mov. 3–5 d/w)	23	91	20	134
500–1500 kcal	15	30	2	47
1500–3000 kcal	8	49	9	66
>3000 kcal	–	–	7	7
I do not know	–	12	2	14
intense activity (intense movement 6–7 d/w)	9	19	9	37
500–1500 kcal	6	5	–	11
1500–3000 kcal	3	9	6	18
> 3000 kcal	–	2	2	4
I do not know	–	3	1	4
very intense activity (intense daily exercise or sports or training twice a day)	1	3	–	4
between 500–1500 kcal	1	1	–	2
between 1500–3000 kcal	–	1	–	1
over 3000 kcal	–	1	–	1

Notes: *Reference Daily Intake. **Days / Week.

For data processing, the variable **In1.** *What type of food do you usually eat?* is dichotomized. Since the study participants are university students, the variable of products ordered online is recoded to include the category of daily supply (Figure 2). Thus, this question measures respondents' online orders for food products (In1R, the dependent variable). The online food category includes both catering and fast food orders via apps or other online methods. The variable **In1R** uses 1 for online food orders and 0 for self-prepared products.

Two years after the start of the pandemic, 17.43% of respondents regularly order food online, while 82.57% cook at home and order online only occasionally. Low income (400–600 /month) and uncertainty about the future (e.g., the war in Ukraine) generally reduce the propensity to spend and explain the need to cook at home. In addition, several restaurants provided food of lower quality than the dine-in meals or failed to provide adequate nutritional information to encourage online food shopping.

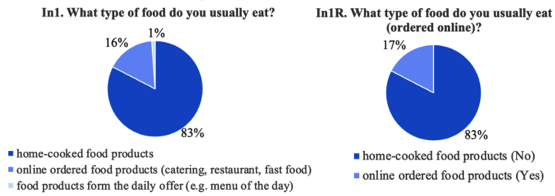

Figure 2. Recode variable In1

The study aims to to predict respondents' preferences for online or at home cooked meals using a regression equation. Thus, the dependent variable (DV) is y = 1 for online ordered food products and meals and y = 0 for food prepared at home. Logistic regression can be used to estimate the probability that a respondent will prefer ordering food online given a set of values of the independent variable (IV). The impact of nutrition labeling on food purchase and consumption may vary depending on the socio-demographic characteristics of the population (gender, age, income). Certainly, campaigns to raise awareness among young people about nutrition, but also education programs aim to promote the use of nutrition labels among students (Smith et al., 2000; Christoph et al., 2015; Christoph & An, 2018). Learning about nutritional information with the help of labels has a significant influence on the selection of food products, people interested in the number of calories consumed being willing to use strategies that include the information on the labels when choosing a food product (Van Der Merwe et al., 2010; Sinclair et al., 2014). A hierarchical logistic regression model will include the dependent variable **In1R** and five explanatory variables (predictors) introduced in three steps. The recoding of DV is done automatically by SPSS (no = 0, yes = 1) with the conventional reference value for logistic analysis 1, and for VI – In2, In13.1, In13.2, In22 – the reference category is "First" and the coefficient of the first category parameter is zero. Thus, in the categorical VI parameterization, each category is treated as a dummy variable with a numerical code. In the regression equation, the codes are used as X values for the dummy variables represented by the categories of the predictor variables (Popa, 2010). The regression coefficient for Income level (1) is equal to the difference between the predicted logit values for students with incomes between 201–400 EUR and those with incomes <200 EUR (Income level 2: 401– 600 EUR; Income level 3: 601–800; Income level 4: >801 EUR). Hierarchical binary logistic regression steps (Figure 3) include explanatory variables to test whether the new model is better than the baseline model.

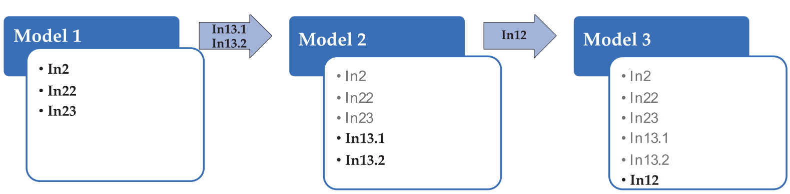

Figure 3. Hierarchical binary logistic regression model

At each step of the model estimation it is tested (Model 1: 82.6%, Model 2: 84.9%, Model 3: 85.4%) to verify whether the shift from the previous model is an improvement. One of the logistic regression significance tests for individual variables is the Wald test (B = –1.556), for the initial regression model construction based on the constant only. In this case, Sig. = 0.000 confirms the model's initial significance. Exp(B) = 0.211 is the ratio of the probability of occurrence to the probability of non-occurrence of the reference event (What type of food do you usually eat?). The model's residual Chi-square test value (16.286; sig.= 0.012 < 0.05) is statistically significant, indicating that one or more IVs may increase its predictive power. It can be observed in Table 3 that the introduction of predictors in the analysis (Model 1–3) leads to a significant improvement in the fit to the reference model.

Table 3. Omnibus tests of model coefficients

		Chi-square	df	Sig.
Block 1: Model 1	Step	16.286	6	.012
	Block	16.286	6	.012
	Model	16.286	6	.012
Block 2: Model 2	Step	43.964	8	.000
	Block	43.964	8	.000
	Model	60.250	14	.000
Block 3: Model 3	Step	2.433	4	.657
	Block	2.433	4	.657
	Model	62.683	18	.000

Step	–2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
Model 1	307.546[a]	.045	.075
Model 2	263.582[b]	.158	.262
Model 3	261.149[c]	.164	.272

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.
b. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.
c. The cut value is .500

The small values of the *R2Cox&Snell and R2Nagelkerke coefficients* (Table 3), similar to the R2 coefficients in the linear regression (Crowson, 2021; Osborne, 2014), indicate that the predictors included in the model explain only 6.3% of the value of the In1R variable (7.4%, respectively).

$$McFadden's_{M1} = \frac{16.286}{307.546 + 16.286} = \frac{16.286}{323.832} = 0.0503\,;$$

$$McFadden's_{M2} = \frac{60.250}{263.582 + 60.250} = \frac{60.250}{323.832} = 0.1861\,;$$

$$McFadden's_{M3} = \frac{62.683}{261.149 + 62.683} = \frac{62.683}{323.832} = 0.1936\,. \quad (1)$$

The Chi-square test shows that the models with DVs have a significant improvement in fit relative to the null model predictors, justifying the shift from the constant-only model to those with predictors. The model fit improved significantly when introducing IV In13.1 and In13.2 into Model 2, compared to Model 1 (containing IV In2 – menu decision, In22 – income level, and In23 – gender), as shown by the chi-square test value of the model likelihood ratio (LR) on row Block, $\chi^2 = 43.964, p < 0.0001$ (Crowson, 2021). At the same time, although for Model 3, $\chi^2(18) = 62.683, p < 0.0001$, the chi-square test value of the model likelihood ratio (LR) located on row Block, $\chi^2 = 2.433, sig. = 0.657 > p = 0.05$ (Crowson, 2021). Model 2 will therefore be taken as the reference model. The Hosmer and Lemeshow Test (Model 1: chi-square = 2.997, Sig.= 0.935; Model 2: chi-square = 6.014, Sig. = 0.646; Model 2: chi-square = 9.604, Sig. = 0.294) certifies the statistical significance of models 1–3 for prediction ($p > 0.05$). The Chi-square test values for the 2LL difference between the original model and the model with predictors, with Sig. <0.05, reject the null hypothesis and accept the model with predictors. Although predictors explain a small part of the DV variation, models with VI are considered to provide an improvement. The correspondence between the observed criterion values and those predicted from the model indicates a high efficiency of the prediction model for Models 2 and 3, with the overall percentage of correct classification being 84.9% for Model 2 and 85.4% for Model 3. The results of the prediction model, presented in Table 4, provide the necessary information for the analysis of each of the predictor variables.

Table 4. Variables in the equation (Model 1–3)

		Model 1				Model 2				Model 3			
		B	Wald	Sig.	Exp (B)	B	Wald	Sig.	Exp (B)	B	Wald	Sig.	Exp (B)
Step 1[a]	In2	–1.417	6.855	.009	.242	–1.949	11.118	.001	.142	–1.937	10.839	.001	.144
	In22		6.581	.160			10.795	.029			9.368	.053	
	(1)	–.248	.370	.543	.781	–.370	.724	.395	.691	–.382	.758	.384	.683
	(2)	.424	1.070	.301	1.527	.802	3.092	.079	2.230	.774	2.724	.099	2.168
	(3)	.166	.107	.744	1.181	.098	.026	.871	1.103	.151	.062	.803	1.163
	(4)	.896	3.561	.059	2.450	1.097	4.362	.037	2.996	1.033	3.647	.056	2.810
	In23	.026	.007	.933	1.026	.162	.207	.649	1.175	.193	.289	.591	1.213
	In13.1						13.551	.009			11.509	.021	
	(1)					–1.326	3.312	.069	.266	–1.178	2.496	.114	.308
	(2)					–2.040	8.278	.004	.130	–1.853	6.181	.013	.157
	(3)					–2.057	8.068	.005	.128	–1.948	6.574	.010	.143
	(4)					–2.968	11.389	.001	.051	–3.085	10.132	.001	.046
	In13.2						20.729	.000			21.145	.000	
	(1)					1.289	5.455	.020	3.629	1.388	5.849	.016	4.006
	(2)					–.215	.125	.724	.806	–.121	.037	.847	.886
	(3)					–.483	.332	.565	.617	–.453	.270	.603	.636
	(4)					1.459	2.284	.131	4.304	1.472	2.243	.134	4.357
	In12										2.408	.661	
	(1)									–.757	1.649	.199	.469
	(2)									–.350	.367	.545	.704
	(3)									–.393	.374	.541	.675
	(4)									.185	.042	.838	1.203
	Constant	–.146	. 030	.863	.864	1.597	1.852	.174	4.939	1.757	2.166	.141	5.795
a. Variable(s) entered on step 1:		In2; In22; In23				In13.1; In13.2				In12			

End of Table 4

Significant variables (Model 1–3)

Model 1	Model 2	Model 3
In2 – Who decides your daily menu?	In2 – Who decides your daily menu? In22 – Income level (level 4) In13.1 How often do you read the nutrition label? [In case of new / unfamiliar products] (levels 2–4) In13.2 How often do you read the nutrition label? [In case of familiar products] (level 1)	In2 – Who decides your daily menu? In13.1 How often do you read the nutrition label? [In case of new / unfamiliar products] (levels 2–4) In13.2 How often do you read the nutrition label? [In case of familiar products] (level 1)

The Wald test for each coefficient combined with the significance level Sig. reveal the variables that have a significant contribution to DV (Table 4). In Model 3, the variable In2-Who decides your daily menu? is significant (p-value < 0.01) and the negative coefficient for In2 indicates an inverse relationship between others deciding the menu and ordering food online. In other words, people who set their own menu are more likely to choose food ordered online instead of cooking at home, compared to people who's menu is decided by others (family, friends). If in the first model the probability of order food online is 0.242 times lower than the probability of cooking at home (Odds ratio = 0.242), for Model 2 and 3 this is approximately 0.14 times lower (0.142, respectively 0.144). This finding highlights the potential influence of social factors on food choices, which complements the exploration of mobile apps to improve sustainability in food consumption (Mu et al., 2019).

In Model 2, category 4 – In22 (Income level), categories 2–4 – In13.1 (How often do you read the nutrition label? [In case of new / unfamiliar products]) and category 2 – In13.2 (How often do you read nutrition label? [For familiar products]) are statistically significant. Income category 4, participants with the highest income (>801 euro/month), has a significant impact on food preferences (p-value < 0.05), compared to the reference category, those with the lowest income (<200 euro/month). This suggests that there is a significant difference in the food preferences of participants with high incomes being 2.996 times more likely to order food online instead of cooking at home compared to participants with low incomes. The participants show significant differences in terms of dietary needs, meal planning, nutritional quality, but showed notable similarities in terms of the influence of the COVID-19, perception of health status and impulse purchases tendency. Cooney (2020) observed also variations and similarities in food purchasing behavior among high-income and lower-income participants. The absence of meal planning and the complexity of cooking can also be the results of a decrease in the level of knowledge and skills regarding food and nutrition. This fact is confirmed by Begley et al. (2019) who found that low food literacy was associated with increased food insecurity. In both Model 2 and Model 3, the significant category coefficients for variable In13.1 show that as the frequency of reading nutrition label information increases, the likelihood of order food online decreases significantly compared to home cooking. Reading nutrition labels appears to influence food preferences and can be considered an essential tool in promoting healthy habits for students, with the potential to shape future food choices (Nelson et al., 2008; Christoph et al., 2015).

Current research tries to understand and anticipate the effects of reading nutrition labels on food preferences. 66.28% of respondents say that the nutrition label has a significant impact on their food choices (home cooked or ordered online), while 33.71% say it has a small impact. Currently, nutrition label does not play a major role in online food purchases. This invalidates the first hypothesis of the study, **H1a – Nutrition labeling significantly and positively influences online food purchases.** The presence of nutritional information online does not change the intentions to buy, but it can direct them toward healthier products given the variety of foods and manufacturers on the market. Consumers used to searching for nutrition labeling are not encouraged to order products through m-commerce because the information is sometimes missing or displayed in an inappropriate/inadequate format. These circumstances make online commerce untrustworthy and uncertain, but at the same time provide an opportunity for mobile apps to provide consumers with the nutritional information that is currently available in physical form, both individually for each food product online and in an appropriate format for digital natives. In this way, nutrition labelling is likely to become an important factor in online food purchases as well. The invalidation of H1a made it necessary to distinguish between two situations that can better explain the attitude of digital natives when buying food online. For example, an inverse relationship was found between interest in nutrition labeling and food consumption decisions when purchasing new/unfamiliar products. This can also be explained by the inconsistent/inadequate implementation of nutritional information online. This confirms the following hypothesis, **H1b – Interest in nutrition labeling for new/unfamiliar products has a significant and negative impact on online food purchases.** The same cannot be said for familiar products, whose online purchase is significantly and positively influenced by interest in nutritional information. For some respondents, the presence of nutritional information online for familiar food products contributes to encouraging their purchase. The following hypothesis is partially validated, **H1c – Interest in nutrition labeling for familiar products significantly and directly (positively) influences online food purchases.**

Income also influences online food purchases. Low income may discourage online food purchases, which are more expensive and require a delivery fee. On the other hand, respondents with higher incomes are more likely to order food online. The analysis includes students, 46% of whom receive only parental financial support, 42% of whom have both parental and own income, and 12% of whom have only their own income. This validates the following hypothesis: **H2 – A higher income level has a significant and direct (positive) influence on the decision to order food online.** As shown in Table 5, income influences the decision to regularly order food online, with a willingness to pay a higher price. A higher income also means a busier schedule and a higher willingness to order food online.

Table 5. Distribution of respondents by income and online food consumption habits

Income level	Order food products online on a regular basis		
	Yes	No	Grand Total
< 200 EUR	16	88	104
201–400 EUR	13	95	108
401–600 EUR	15	52	67
601–800 EUR	7	30	37
>801 EUR	10	24	34
Grand Total	61	289	350

The finding of a statistically non-significant value in Table 4 for the gender variable (IV – I23) leads to the invalidation of hypothesis 3. This could indicate a similar interest between the two categories (men and women) for both home-cooked and online ordered food. Thus, the following hypothesis is invalidated, **H3 – Women are more hesitant to order online because they lack adequate nutrition labeling.**

The decision to set one's own menu (IV – In2) is an important variable that has a statistically significant coefficient, leading to the validation of the following hypothesis, **H4 – Responsibility for setting one's own menu has a significant and direct (positive) impact on online food ordering choices.**

As shown in Table 6, individuals who set their own menus are more likely to order food online (20%) than individuals whose menus are set by others (6%), e.g., family members, friends, etc. This can also be explained by the difficulty of allocating time for food preparation, perhaps a lack of preparation skills, or the adoption of a more dynamic and pragmatic lifestyle.

Table 6. Distribution of respondents by menu decision and online food consumption habits

Who decides the daily menu	Order food online on a regular basis		
	Yes	No	Grand Total
I decide my own menu	20%	80%	281
Other people (family, friends) decide my menu	6%	94%	69
Grand Total	61	289	350

Since the daily menu is 80% determined by respondents, it is important to identify the main factors influencing food consumption and whether a mobile app with nutritional information is the appropriate way to improve the nutrition label. Digital natives are also changing their diets, replacing or even abandoning products that take more time to prepare with others that are easier to prepare or available online.

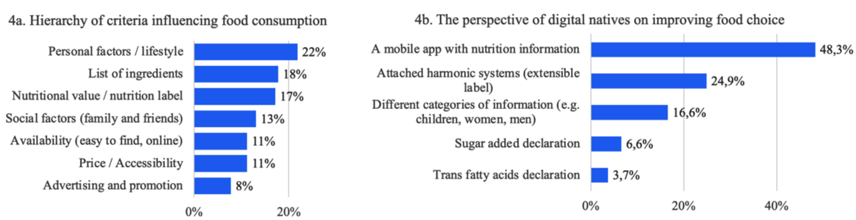

Figure 4. Factors influencing food consumption and methods to improve it for digital natives

Figure 4a shows that after personal and lifestyle factors (e.g., food preferences, reduction in time spent eating, and meal preparation), ingredient list and nutrition labelling remain very important criteria influencing food consumption. Non-parametric correlation analysis shows medium-intensity direct relationship between availability (ease of finding the product) and price, lifestyle, and ingredient list, which are the most important factors in food choices for digital natives. Although nutrition label does not have a significant impact on online food availability, it is strongly correlated with ingredient list, and proper integration of nutritional information would positively influence online food choice. These findings are in line with previous research that found time management and lifestyle, health status, and income level to be the most important factors influencing the food consumption decisions of generation Z (Bumbac et al., 2020). In response to the question *What do you think are the most appropriate* *ways to improve the nutrition label?*, 48.3% of respondents considered a mobile app detailing nutritional information necessary. According to the hierarchy in Figure 4b, digital natives prefer an app that provides nutrition information details in a user-friendly way to improve nutrition labeling. Integrating nutrition information through m-format nutrition labeling as a dedicated app model can address the key factors that influence online food purchases: advertising, promotion, and availability. This confirms the last hypothesis, **H5 – Adapting the nutrition labeling for mobile devices (m-format) is a crucial step in meeting the expectations of digital native consumers and improving their overall shopping experience.**

The research objectives were met, and 3 of the 6 hypotheses were validated, 1 partially validated, and 2 invalidated. According to Shangguan et al. (2019) nutritional labeling reduced consumer energy intake by 6.6%, total fat intake by 10.6%, and unhealthy dietary options by 13.0%. It also increased vegetable consumption by 13.5%, reduced salt content by 8.9% and decreased trans fat by 64.3% (Shangguan et al., 2019). This is why digital natives lack of importance in nutrition labels, as shown by the invalidation of H1a, is a real issue that needs to be addressed. To promote healthier lifestyle among younger generations, substantial efforts should be made to adapt information to their communication and usage preferences. Given the prevalent use of mobile devices, e-commerce has shifted to m-commerce. Digital natives are interested in the nutrition labeling of new or unfamiliar products, which often leads them to abandon the purchase (validation of *H1b*). Digital natives' personalities demand more transparency, fairness and sufficient information in decision making. All these aspects require a new communication channel adapted to their preferred digital environment. The partial validation of *H1c* shows that nutrition labeling in familiar foods can positively influence purchase decisions. Nutrition labeling in a mobile-friendly model would increase trust in online shopping. *H2* shows that the benefits of buying food online come at a higher cost. For this reason, online shopping, even if available, cannot become a habit at the expense of preparing food at home. At the other end of the spectrum, higher income levels, often combined with busy schedules, contribute to the propensity to order food online. Invalidation of *H3* shows that men and women have similar attitudes toward online food order, indicating a general trend toward food m-commerce. When choosing between online or home-cooked food, independence and responsibility in setting your own menu are crucial. *H4* confirms that people who set their own menu are more likely to order food online than people who do not. Price, lifestyle, and ingredient list are key criteria for digital natives when choosing food. Just as physical nutrition labels improve awareness and understanding of nutrition information, they do not change purchase intent, but can redirect them toward healthier food choices, so would the implementation of m-format nutritional labeling create the conditions for an online balanced eating behavior as demonstrated by the validation of *H5*. The online availability of nutrition labeling could create the conditions for digital natives to eat healthier and more conveniently. Thus, the implementation of m-format nutrition labeling would combine the simplicity and ease of receiving the message with additional information (preparation methods, product associations, calorie control, etc.). The digital native can easily use this information in apps to improve their health and awareness in a friendly, simplified and personalized way. The possibility of interlinking mobile apps that contain food nutrition and health data would enable personalization of dietary needs, facilitating a balanced diet for consumers. In addition, by analyzing the data collected by such apps, nutrition standards could be updated and food and nutrition policies could be better adapted to national circumstances.

5. Implications

Consumer behavior changes the food industry, necessitating a re-evaluation of the connection between producers, retailers and consumers in a digital environment that thrives on multi-channel communication. M-format nutrition labeling is crucial for improving this relationship by enhancing customer shopping experience through a "hyper-personalization" (Iglesias-Pradas & Acquila-Natale, 2023) that will transform food m-commerce.

For mobile app developers, m-format nutrition labeling would enable greater integration (e.g. in meal planning apps, restaurant and food delivery apps, health and fitness apps), providing comprehensive food information and allowing users to effortlessly track, understand and optimize their dietary habits. This innovative approach not only improves the accessibility of nutritional data, but could also facilitate automatic diet monitoring, paving the way to a more health-conscious lifestyle. In this regard, it is essential for app developers to collaborate with nutritionists, food manufacturers and retailers. This would ensure the accuracy and relevance of the nutritional information provided to end users.

The results of this study can help policy makers to formulate future guidelines and regulations for food labeling on m-commerce platforms. Such initiatives aim to enforce uniformity, consistency and accessibility of information through nutritional labeling in m-format. This standardized approach not only promotes collaboration between different sectors and the use of advanced technologies, but could also facilitate the generation of data on dietary trends, nutritional deficiencies or excess intake of certain nutrients in the population. Therefore, such information could help policy makers to make informed decisions in food and health policy, enabling targeted support and the promotion of healthier eating habits. M-format nutrition labeling is in line with the European Union's priorities in promoting a creative and informed young generation by encouraging active, reflective and critical thinking and developing their ability to evaluate nutritional information (The Council of the European Union, 2019).

6. Conclusions

The research sustains adapting and integrating nutrition labeling by translating it into a user-friendly, easy-to-understand, and digital format. Moreover, the predominant use of mobile devices and the already common practice of purchasing food online require an update of the nutrition label. Thus, this article proposes a new concept, that of m-format nutrition labeling, to develop and use nutritional information in a way that is relevant to our times and promotes a healthy lifestyle. Digital natives don't value nutrition labeling when buying food, which raises questions about encouraging healthy and responsible food consumption. However, the increased interest in nutrition labeling for new products has a negative effect on the purchase decision, indicating that nutrition information influences consumption decisions. This research also emphasizes the importance of menu responsibility and a higher income on the preference for online food purchases for both women and men. Nutrition labeling would not change purchase intentions, but it would satisfy the need for convenience and a healthier diet. Nutrition labeling remains the essential way to inform and educate, raise awareness, and empower consumers. With a technological update, it can correct and improve the shopping experience of digital natives. More specifically, there is a need to adopt an m-format nutrition label that has a smart visual format, can integrate artificial intelligence, is mobile-ready, can be linked to other applications, is trustworthy, user-friendly, easy to understand, and is attractive to both customers and policymakers.

In terms of research limits, the study is restricted to a particular cultural and geographical setting, focusing on digital natives with higher education and knowledge in nutrition, using a relatively small data sample size that may lead to increased variability in coefficient estimates. Therefore, the results may not accurately reflect a broader young consumer population or other age groups due to differences in cultural views, use of technology and attitudes towards nutrition labeling. The correlation between m-commerce food procurement and nutrition labeling has not been extensively studied, making predictors identification a challenging task. There may be other influencing factors not considered in the study that may affect online food order, the use of nutrition labels and technology. Measuring subjective aspects such as online shopping experiences and different food consumption patterns is challenging, and probably higher accuracy would require more advanced methods and means to identify and interpret the influencing factors. As a result, the logistic regression model partially explains the dependent variable, and the best fit model reveals only three significant predictors. Like other studies looking at technology and consumer behavior, this study offers valuable insights, the relevance of which may be influenced over time by the evolution of technology and ever-changing consumer habits.

The research can be further extended by integrating more variables and by extending the research to different age groups, levels of education, dietary habits, technological skills and cultural backgrounds. This would provide insights into the differences in behavior, food perceptions and preferences at different stages of life. The research can be enhanced by including qualitative data, such as interviews, to gain more comprehensive insights into subjective perspectives. The research can be repeated over time to monitor development and understand changes in the use of labels adapted to new technologies. Future research can look at the development of smart labels that integrate QR codes, RFID tags, wireless communication and sensors improving data collection and consumer engagement. Through the use of augmented reality and smart devices, digital labels could provide quick access to detailed product information, boost consumer confidence and encourage healthier choices. Future research could explore the benefits of digital labeling in the context of the development of artificial intelligence and its ability to recognize consumption patterns that match individual consumer profiles, to optimize food intake according to personal needs. Future studies on this topic could have a significant impact on the formulation of coherent nutrition labeling policies, creating targeted nutrition education programs for different generations of consumers and ultimately contributing to the improvement of overall human health.

Author contributions

Magdalena Bobe: Conceptualization, Validation, Formal analysis, Writing – Original Draft, Resources. Roxana Procopie: Conceptualization, Investigation, Writing – Original Draft, Visualization, Resources. Rodica Pamfilie: Conceptualization, Writing – Review and Editing, Supervision. Robert Bumbac: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – Original Draft, Visualization. Smaranda Giușcă: Conceptualization, Writing – Original Draft, Writing – Review and Editing, Visualization. Mihaela Mihai: Methodology, Formal analysis, Writing – Original Draft. Alexandru Jurconi: Writing – Review and Editing, Visualization, Resources.

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Authors declare that there is no competing financial, professional, or personal interests from other parties.

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