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"I don't know", "I'm not sure", "I don't want to answer": a latent class analysis explaining the informative value of nonresponse options in an online survey on youth health

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ABSTRACT
Online surveys are increasingly used to investigate health conditions, especially among young people. However, this methodology presents some limitations including item nonresponse concerning sensitive and knowledge-related questions. This study aimed to suggest latent class analysis as the methodology to statistically deal with item nonresponse data, while describing item nonresponse in an online health survey addressed to young people. We used data from an e-cohort study on 8,663 French university students and identified six homogenous groups of students with similar use of nonresponse options ('I don't know', 'I'm not sure', or 'I don't want to answer'): one of High Respondents (64.2%), four of Partial Respondents (34.3%), and one of High Nonrespondents (1.5%). Item nonresponse largely depended on the survey's contextual features (type of nonresponse options, question domains), and was significantly associated with (non)respondents' individual characteristics (gender, age, field of study). We conclude that item nonresponse can be very informative and that latent class analysis is a useful method to identify its patterns in online health surveys.

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Nonresponse; online survey; health survey; young people; latent class analysis

Introduction

Online health surveys on young people and nonresponse

When designing a research study, the choice of the survey mode is crucial and must take into account the study's target population and the topic of interest.

Studies on young people are taking advantage of the benefits of the Internet and information technology. Young adults are a highly connected population (McMorris et al., 2008; Van Selm & Jankowski, 2006; Wyatt, 2000) and University students in particular are a very captive audience for online surveys since they are at ease with web-based technologies for their academic and social life (Lai & Hong, 2015). While for other target populations quantitative studies conducted on the Internet might present the risk of a selection bias, representativeness of respondents is supposed to be higher among already avid Internet users (Larson et al., 2011; Pealer & Weiler, 2003). Compared to other survey modes, online surveys allow obtaining in a relatively standardized way, in a short amount of time and without geographical limitations, a considerable quantity of information from large samples of young adults (Evans & Mathur, 2005; Wright, 2005).

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Concerning the topic of the research study, online surveys seem to be an effective format to ask respondents about difficult to discuss themes, e.g. sexual and mental health (Rhodes, Bowie, & Hergenrather, 2003). Notably, previous studies have shown that young people are prone to answer sensitive and knowledge-related questions concerning their health in online self-administered questionnaires (Regmi, Waithaka, Paudyal, Simkhada, & Van Teijlingen, 2016; Van Gelder, Bretveld, & Roeleveld, 2010). These studies suggest that the online survey mode is preferable for sharing personal information and experiences compared to face-to-face interviews, thus reducing social desirability bias. Possible reasons include the anonymity of both participant and researcher which may increase levels of self-disclosure and decrease the feeling of stigmatisation (Birnbaum, 2000).

Despite the advantages just outlined, there are considerable challenges generated by online health surveys addressed to the general population and young people in particular. The bulk of the literature on survey methodology has identified and described several concerns including ethical considerations, technological issues, potential biases and data quality (Eysenbach & Wyatt, 2002; Hamilton, 1999; McInroy, 2016). Among these drawbacks, nonresponse represents a significant problem for online surveys to the same degree as for traditional paper questionnaires (Coste, Quinquis, Audureau, & Pouchot, 2013; Denscombe, 2009; Dillman, Eltinge, Groves, & Roderick, 2002; Hohwü et al., 2013).

Types of nonresponse and reasons for addressing item response in online health surveys on young people

There exist two main types of nonresponse in survey research: unit and item nonresponse (Yan & Curtin, 2010). Unit nonresponse is also defined as total nonresponse or nonparticipation and corresponds to an unsuccessful attempt to obtain desired information from a person from a pre-defined sample (Fraenkel, Wallen, & Hyun, 1993; Groves, Dillman, Eltinge, & Little, 2002; Singer, 2006; Toepoel & Schonlau, 2017). Unit nonresponse can be due to participants' lack of time, interest, willingness or trust towards the survey, as well as researcher's inability to contact the sample or survey non-coverage (Simeoni, 2016). On the other hand, item nonresponse refers to the absence of answers to specific questions (or items) in the survey after a person from a pre-defined sample agrees to participate in the study (Groves, Singer, & Corning, 2000). This lack of a valid answer on online surveys could be due to: (1) technical hardware and software problems while completing the survey or storing the data; (2) questionnaire interruption or skip of due question by the participants; or (3) the refusal of participants to provide information about specific questions by using noncommittal replies (Denscombe, 2009; Shoemaker, Eichholz, & Skewes, 2002). While in the first two cases of item nonresponse the participant is 'passive' and blank cells or missing values are displayed in the final survey database, the third reason corresponds to the participant's 'active' use of noncommittal replies such as the answer options 'I don't want to answer' (DWA), 'I don't know' (DK) or 'I'm not sure' (NS).

A considerable amount of survey research has explored the causes and consequences of both unit nonresponse and item nonresponse exclusively for blank cells or missing values (reasons 1 and 2) across different topics and target populations, in traditional as well as online surveys (Beatty & Herrmann, 2002; Coste et al., 2013; Dillman et al., 2002; Dillman, Smyth, & Christian, 2009; Kalb, Cohen, Lehmann, & Law, 2012; LaRose & Tsai, 2014; Singer, 2006). The causes concern the phase prior to data collection (e.g. above-mentioned non-coverage, inability to contact the participant), whereas the consequences concern the phase post data collection and correspond to the conception and use of statistical techniques to obtain less biased estimates like imputations and reweighting procedures (Groves et al., 2002; Toepoel & Schonlau, 2017).

Nevertheless, item nonresponse generated by participants deliberately and actively using noncommittal replies (reason 3) is less well documented (de Leeuw, Hox, & Boeve, 2016; Francis & Busch, 1975; Gilljam & Granberg, 1993; Yan & Curtin, 2010), with sparse studies on the specific health sector (Couper, 2017; Van Gelder et al., 2010). Additionally, research on this type of item nonresponse in online health surveys addressed to young people is almost inexistent (McMorris et al., 2008; Shoemaker et al., 2002).

Given this gap in the literature and with the current rise in the use of web-based questionnaires in the health sector addressed to young people (McInroy, 2016; Pealer & Weiler, 2003), exploring the causes and consequences of item nonresponse in online health surveys among youth has an added significance.

Indeed, researchers have been debating the role of DWA, DK and NSA options for years (Singer, 2006). Some argue that noncommittal replies contribute to reduce the statistical power of survey studies, by decreasing sample size, and cause biases if item nonrespondents differ from full respondents. In other words, DWA, DK and NSA options are survey errors to impute (Coste et al., 2013). For some others, these options can contribute to the quality and validity of collected data since they give respondents the possibility to complete their survey without feeling forced to provide a straight answer (Dillman et al., 2002). Compared to noncommittal replies, 'forced answers' go against the norm of voluntariness in a survey and may annoy respondents. The use of DK, NS and DWA options is then considered as an ethical choice (DeRouvray & Couper, 2002) and a useful mean for researchers to obtain at least a partial, but reliable and valid response (de Leeuw et al., 2016), which also provides non-ignorable information (McMorris et al., 2008). Thus, the debate on the use and the utility of noncommittal replies is still open.

Definition of item nonresponse options and rates

In all types of surveys, and particularly in health-related ones, the nonresponse options DK, NS and DWA are strictly linked to the nature of the question (Presser et al., 2004) and must be distinguished. The DK option allows respondents to state that they have no clue about a particular issue. The fact of answering DK has a basic cognitive explanation: the respondent is actually and genuinely not able to answer (Beatty & Herrmann, 2002). The DK option is usually included in knowledge-related questions. The NS option is a response which does not force uncertain survey respondents to provide a precise and definitive answer (Groothuis & Whitehead, 2002). The difference with the DK answer is subtle: while the DK option best suits factual questions (e.g. questions on family medical history), the NS option is more adapted for attitude questions (e.g. questions asking one's opinion about compulsory vaccination), and allows respondents to state that they are undecided on an issue they have already thought about without coming to a final conclusion. Finally, DWA corresponds to a real strong refusal to answer and is mostly included in sensitive questions, e.g. questions on one's alcohol and drugs use or sexuality (Tourangeau & Yan, 2007). All three nonresponse options may also be due to a lack of motivation, since participants may prefer not going to the process of providing a valid answer. In other words, item nonresponse could also be explained by the leverage-salience theory (Groves et al., 2000) stating that people might be more or less interested in the surveyed topic: if the topic is not of interest, people may tend to use more nonresponse options (Groves, Presser, & Dipko, 2004).

Health-related surveys generally include numerous knowledge-related and sensitive questions that respondents might find difficult to answer. For this, survey researchers have long advocated the use of self-administered questionnaires in order to maximize truthful responding to health questions (Willis, Al-Tayyib, & Rogers, 2001). The Internet facilitates self-administration and even for this reason, online health surveys are more and more used by researchers interested in population health (McMorris et al., 2008). Introducing the DK, NS and DWA options is then important to ensure participants that they are free to express their opinion and that they have the right not to openly disclose personal information, even within a supposedly anonymous digital environment.

A few studies have reported data on item nonresponse rates generated by noncommittal replies in online surveys addressed to young people in different fields, including the health sector.

Heerwegh and Loosveldt (2008) have questioned students on their attitudes toward immigrants and asylum seekers through an online questionnaire and compared their results with those of a control group answering the same questionnaire offline. Results showed that web survey respondents produced a higher DK response than offline respondents (.174 versus .068). Denscombe (2009) used the same comparative approach for his study on item nonresponse in near-identical questionnaires delivered online and offline on the use of tobacco and alcohol and the way this is associated with young people's self-identity and perceptions of risk. Results were opposite to those of Heerwegh and Loosveldt (2008): the online mode of administration produced lower item nonresponse rates than its paper-based counterpart, especially for fixed-choice questions (paper = 2.7%, online = 1.5%). McMorris et al. (2008) also compared web and in-person survey modes to gather data from young adults on sex and drug use finding no significant difference between the two approaches. Finally, Joinson, Paine, Buchanan, and Reips (2008) described students' use of an 'I prefer not to say' option to sensitive questions. They found that income was the item most commonly non-disclosed to (37.5% of responses were 'I prefer not to say'). This was followed by religiosity (10.7% non-disclosure) and ethnicity (3.9% non-disclosure). Similarly, other studies concerning the use of noncommittal replies in online surveys, across different target populations and topics (e.g. politics, economy) have produced conflicting results (de Leeuw et al., 2016; DeRouvray & Couper, 2002; Groothuis & Whitehead, 2002; Hohwü et al., 2013; Shoemaker et al., 2002; Waters, Hay, Orom, Kiviniemi, & Drake, 2013).

Using latent class analysis to describe item nonresponse

Statistical techniques to handle item nonresponse produced by noncommittal replies have not been clearly identified and described, yet, apart from classic descriptive statistics and multivariate logistic regressions (Waters et al., 2013).

Latent class analysis (LCA) (Goodman, 1974; Lazarsfeld & Henry, 1968) is a model-based approach which can be used to classify individuals in latent classes based on observed response patterns in a set of categorical variables/items (Collins & Lanza, 2010; McCutcheon, 1987). For identifying the groups and their response patterns, LCA assumes a local independence or conditional independence, i.e. the observed categorical items are mutually independent once the categorical latent variable is conditioned out, or the variables are independent within each latent class. In this type of analysis, the starting hypothesis is that we are dealing with a mixture of subpopulations (i.e. the latent classes) and that their differences in the patterns of item (non) response are explained by the fact that each individual belongs to one or more latent classes. In turn, each class corresponds to a specific pattern of item (non)response. From this point of view, LCA can also be considered as a type of cluster analysis (CA) by means of finite mixture density models for categorical data (Everitt & Hothorn, 2011). However, unlike traditional CA, LCA identifies subgroups based on posterior membership probabilities rather than ad hoc dissimilarity measures such as Euclidean distance. The general probability model underlying LCA allows for formal statistical procedures for determining the number of clusters, and more interpretable results stated in terms of probabilities. LCA is designed to try to explain with one (or several) latent variable(s) the non-independence of a set of dichotomous variables that can act as indicators or markers of the latent variable. This is the main difference between LCA and CA (Fonseca, 2013). Furthermore, in CA we use distances and procedures to obtain the groupings, while in LCA we use a more precise method, because we try to explain the non-independence between indicators of a phenomenon that we are interested in based on the existence of differentiated groups (Magidson & Vermunt, 2002). As a latent structure model, LCA is also similar to common factor analysis (CFA) because both estimate latent variables from a set of indicator variables (Vermunt & Magidson, 2005). In CFA, latent variables are continuous and are called factors, while in LCA they are categorical and are called latent classes. An important difference is that CFA is focused on grouping items into factors, and therefore it is a variable-centered approach (i.e. focused on relationships among variables and not among individuals), while LCA is focused on grouping subjects or cases based on item response patterns, and therefore is a person-centered approach (Wang & Wang, 2012). Thus, the main advantage to using LCA is that it can identify distinct groups across multiple behaviours or characteristics that can be examined simultaneously and not separately (Fitzpatrick et al., 2015).

LCA has been used in numerous studies concerning young people (Patrick, Bray, & Berglund, 2016; Shin, McDonald, & Conley, 2018) and in the last few years its use is growing (Nylund-Gibson & Choi, 2018).

The objectives and hypotheses of this study

This study was aimed to propose LCA as an effective statistical technique to deal with item nonresponse data in online health surveys addressed to young people. Hence, the LCA methodology was applied in order to: (1) define nonrespondent patterns (or classes) in relation to nonresponse options and question domains; and (2) describe the patterns obtained according to (non)respondents' individual characteristics. We hypothesized that the highest rates of DK and NS answers would be reported in knowledge-related items, while the highest rates of DWA answers in sensitive questions. We also hypothesized that the use of these three options of item nonresponse would be significantly correlated with the characteristics of the respondents and, in particular, that younger, male and non-health-related students would report the highest rates of DK, NS and DWA answers.

The application of the LCA methodology to verify these hypotheses would contribute to the methodological knowledge on the informative value of item nonresponse options and, most of all, on the utility and efficacy of LCA in addressing item nonresponse in online health surveys. Furthermore, clearly understanding whether the use of item nonresponse is determined by survey's contextual features (types of nonresponse options, question domains), and respondents' characteristics (gender, age, field of study) would help designing future online health surveys addressed to young people and students in particular.

Methods

The i-Share project

Our study used data retrieved from the i-Share (Internet-based Students Health Research Enterprise) project, which is an ongoing online survey started in 2013 and aimed to collect longitudinal data on the health of university students in the whole of France. Participation is voluntary and anonymous. To be eligible to participate, a student has to be at least 18 years of age, and be able to read and understand French. Students are informed about the purpose and aims of the project by flyers, information stands at University registrations, during lectures, and via social media and newsletters. All these supports display the project website (www.i-share.fr). Registration is conducted in two steps: firstly, an online portal pre-registration is required on the i-Share website; secondly, each student completes the self-administered online questionnaire. Every student has to sign an online consent form before starting the questionnaire. The i-Share project was approved by the French National Commission of Informatics and Liberties. The dataset for our analyses included data collected until July 25th, 2017.

Survey's contextual characteristics: nonresponse options across question domains

Our online health survey asks information on the participant's health status, personal and family medical histories, socio-demographic characteristics, and lifestyle habits. It is made up of 135 questions selected by a pool of public health, epidemiology and mental health researchers based on existing questionnaires (e.g. Beck & Richard, 2013) and scales (e.g. ASRS by Kessler et al., 2005), as well as new ad hoc questions. The Delphi technique was applied to construct the questionnaire (Hasson, Keeney, & McKenna, 2000). In the period 2011–2012, several focus groups were conducted with male and female University students from different study fields to assess, through a qualitative approach, the feasibility of the questionnaire, especially in terms of clarity of the instructions, sensitivity of the questions and difficulty of answering questions requiring memory retrieval. During a pilot phase, the online questionnaire was also tested by statisticians and computer engineers. The focus groups and pilot phase were also aimed to include nonresponse options (DK, NS, DWA) in sensitive and knowledge-related questions, in addition to questions already presenting nonresponse options in their original English version, i.e. the ICHD on migraine status (Headache Classification Committee, 2013). The inclusion of nonresponse options was considered all the more important since it was decided to use forced response in order to limit missing values and get the most complete database possible (Heerwegh & Loosveldt, 2008). Providing participants with a noncommittal reply option was intended to reduce wrong answers or even dropouts in our online survey (Stieger, Reips, & Voracek, 2007).

The 135 questions of our online health survey generated 550 statistical variables resulting from the presence of conditional questions, multiple-choice questions or dichotomous questions. In a first screening analysis, we identified ‘usable’ values, eliminating both non-applicable answers (blank values due to conditional questions) and missing values (non-stored data values which were not registered because of technical problems, bugs or involuntary logouts). The main objective of this recoding was to verify that item nonresponse was calculated only on ‘usable’ values.

Then, we identified 51 variables corresponding to 51 questions which included at least one of the three nonresponse options: 20 questions containing the DK option, 6 questions the NS option, and 25 questions the DWA options. These 51 variables were categorized into five domains: Family (FAM), Mental Health & Migraine (MHM), Consumptions (CONS), Health Administrative Issues (ADM), and Sexual Life (SEXL). Figure 1 illustrates how the three nonresponse options are distributed across the five domains.

(Non)respondents’ individual characteristics

We considered the three following demographic variables with the purpose of analysing their relationship with the classes obtained with the LCA: gender (male/female), age (18–19, 20–21, 22–23, 24–30), and field of study (Humanities and Letters, Life Sciences, Medicine, Science Technology, Economy and Law, Other). We opted for these variables since they provide a basic

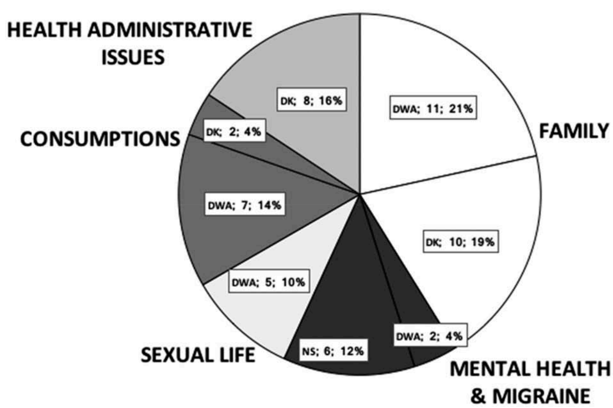

Figure 1. Distribution of nonresponse options (DK, NS, DWA) in the i-Share online health survey across five domains.

description of University students, i.e. our study population. These covariates are used as an example of how the LCA variables can be used.

Of the 8,770 students who completed the questionnaire, the final sample size of our study was 8,663, after eliminating students who were aged <18 or >30 years old (N = 107). Of the 8,663 participants, 75.1% (n = 6,505) were female. The mean age of the total sample was 20.71 (SD 2.24). The distribution by field of study was: 30.5% Humanities and Letters, 20.3% Life Sciences, 15.8% Medicine, 14.0% Science Technology, 10.9% Law and Economy, and 8.6% Other.

Statistical analysis

First, we performed descriptive analyses to examine the distribution and prevalence of item nonresponse. We initially performed Poisson regression models (with inflated zero) as well as multinomial and binomial logistic regressions, but they did not present a good adjustment and did not actually allow providing response patterns according to NR types and the different domains of the questionnaire. This is the reason why, after having tried these regression models, as well as descriptive solutions with some hierarchical and non-hierarchical cluster procedures (k-means), we proposed the use of LCA. LCA allowed the identification of specific classes based on the scores of the 51 binary variables. We evaluated a 1-class model so as to obtain the initial model quality criteria, i.e. Akaike information criteria (AIC), Bayesian information criterion (BIC) and adjusted BIC (aBIC). Afterwards, we increased the number of classes step by step until we obtained the parameters with the lowest values, indicating the best fit of the model. We also used the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT), and the Bootstrapped Likelihood-Ratio Test (BLRT) (Lo, Mendell, & Rubin, 2001), suggesting that, for a $p < 0.05$, the model with more classes fits the data better than the model with fewer classes. In addition to these fit statistics, we examined the value of entropy. This parameter ranges from 0 to 1: values higher than 0.80 indicate that groups are well separated (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993). Once the classes were identified, we obtained the latent class (LC) membership probabilities, and the probabilities of particular (non)responses to observed variables, given membership in a particular LC (Lanza & Cooper, 2016). We also obtained the probabilities of class membership of each individual, which allowed the identification of a categorical variable within classes, by assigning to each student the class with the highest membership probability. This variable permitted to investigate the association of gender, age and field of study with the classes, by using, first, a chi-square test and, second, a multinomial multivariate model (Wald test) to assess the association of these three variables with the classes. The most prevalent group was used as the reference value.

We used Mplus program, version 7.2, to perform LCA (Muthén & Muthén, 2012), and SAS (V.9.4; SAS Institute Inc., 2013) and SPSS, version 24 (V.24; SPSS Inc., 2016) to perform the descriptive analyses and assess the associations between the variables gender, age and field of study. In all analyses, we considered a $p < 0.05$ to be statistically significant.

Results

Table 1 illustrates the prevalence of item nonresponse produced by the 51 variables of our online survey, according to the three options (DK, NS, and DWA) and the five domains (FAM, MHM, CONS, SEXL, and ADM).

Table 2 shows the model quality criteria described in the methodology, as well as the test to decide the best number of classes. The tests on the number of classes (LMRa-LRT and BLRT) were all significant for the solutions of 1 to 7 classes, but not starting from 8 classes, which suggested opting for a solution of <8 classes. Taking into account the model quality criteria (AIC, BIC and aBIC), the high values of entropy from 0.8 in all models starting from 3 classes, and finally the interpretability of the latent classes, a 6-class model was selected. We especially

Table 1. Distribution of nonresponse rates per option and domain (N = 8,663).

	% (n/usable values)	
Family		
DK		
Father's disease episodes	21.6%	(1870/8663)
Mother's disease episodes	16.5%	(1432/8663)
Siblings' handedness*	15.8%	(426/2688)
Parents' handedness*	5.4%	(211/3890)
Family education levels**	5.3%	(443/8382)
Reason of siblings' death	5.2%	(8/155)
Father is alive, age**	5.0%	(417/8290)
Reason of mother's death*	4.1%	(5/121)
Reason of father's death*	3.2%	(10/315)
Mother is alive, age**	2.4%	(207/8510)
DWA		
Reason of siblings' death	5.2%	(8/155)
Divorced/separated parents	3.1%	(268/8663)
Father's disease episodes	2.5%	(220/8663)
Reason of mother's death*	2.5%	(3/121)
Mother's disease episodes	2.5%	(213/8663)
Reason of father's death*	1.9%	(6/315)
Family support	1.7%	(143/8663)
Presence of siblings	1.2%	(108/8663)
Living place during childhood	0.4%	(32/8663)
Mother is alive	0.4%	(31/8663)
Father is alive	0.1%	(57/8663)
Mental Health & Migraine		
DWA		
Suicidal thoughts or attempts	5.2%	(448/8663)
Consulting a psychiatrist**	1.3%	(109/8662)
NS		
Migraine – side of the head*	17.9%	(670/3735)
Migraine – aggravated*	16.7%	(623/3735)
Migraine – pulsatile*	13.3%	(496/3735)
Migraine – nausea*	9.3%	(346/3735)
Migraine – very strong*	8.7%	(326/3735)
Migraine – light or noise*	8.6%	(323/3735)
Sexual Life		
DWA		
Age of first sexual intercourse*	3.3%	(286/6579)
Number of female/male partners*	2.9%	(251/6579)
Sexual intercourses	3.6%	(312/8663)
Emergency contraception *	0.8%	(66/6505)
Abortion*	0.6%	(48/6505)
Consumptions		
DK		
Intention to quit smoking*	11.9%	(288/2415)
Involuntary psychoactive substance consumption	3.3%	(283/8663)
DWA		
Other drugs consumption*	5.2%	(25/479)
Lifetime cannabis consumption	1.4%	(120/8663)
Lifetime psychoactive substances use	0.9%	(75/8663)
Type of psychoactive substances	0.6%	(52/8663)
Recent cannabis consumption*	0.5%	(26/4831)
Hurt because of alcohol*,**	0.3%	(10/3649)
Involuntary psychoactive substance consumption	0.2%	(14/8663)
Health Administrative Issues		
DK		
Vaccination Measles-Mumps-Rubella	19.4%	(1682/8663)
Complementary insurance	18.9%	(1641/8663)
Vaccination Hepatitis B	13.1%	(1135/8663)
Vaccination Papillomavirus*	11.0%	(713/6050)
Social insurance	7.2%	(623/8663)

(*Continued*)

Table 1. (Continued).

	% (n/usable values)	
Scholarship*	5.5%	(176/3196)
Weight and height**	4.8%	(417/8637)
Child health record booklet	2.6%	(224/8663)

*These 22 questions reported non-applicable values, i.e. blank values due to conditional questions, ranging from 6.7% (n = 582) to 98.6% (n = 8542). **These six questions reported missing values due to technical problems interfering with data recording. Missing values ranged from 0.01% (n = 1) to 4.3% (n = 373), with the exception of the variable 'Hurt because of alcohol' reporting the highest number of missing values (51.1%; n = 4432).

Table 2. Values of the model quality criteria to determine the number of classes.

Model	AIC	BIC	aBIC	p (LMRa-LRT)	p (BLRT)	Entropy
1 class	117,551.885	117,912.292	117,750.223	–	–	–
2 classes	112,283.476	113,011.358	112,684.042	0	0	0.706
3 classes	110,258.8	111,354.156	110,861.594	0	0	0.812
4 classes	108,684.188	110,147.019	109,489.21	0	0	0.831
5 classes	108,043.25	109,873.555	109,050.499	0	0	0.854
6 classes	107,587.88	109,785.659	108,797.356	0.0018	0.0019	0.836
7 classes	107,216.976	109,782.231	108,628.681	0.0001	0.0001	0.812
8 classes	106,856.805	109,789.533	108,470.737	0.1843	0.1855	0.829

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; aBIC = adjusted Bayesian Information Criterion; LMR LRT = Lo-Mendell_Rubin Likelihood Ratio Test; BLRT = Bootstrapped Likelihood Ratio Test.

considered interpretability as an important criterion for the selection of the LCA model, reassured by the fact that values of quality criteria were similar for both 7- and 6-class models. In particular, entropy was slightly higher for 6 classes compared to 7 classes.

Table 3 presents the conditional probabilities in each of the 6 classes, considering the question domains and the nonresponse options.

Class 1 (High Item Respondents) was the most prevalent class (64.2%) and was composed of students who almost always answered the survey questions, even if they were provided with a nonresponse option, thus reporting the lowest probability of using item nonresponse. In particular, among the questions presenting the option DK within the FAM domain, the percentages ranged from 0.0% ('Reasons of father's death' and 'Mother is alive, age') to 10.6%. The percentages were between 6.6% ('Migraine – light or noise') and 14.3% ('Migraine – sight of the head') for the questions presenting the option NS within the MHM domain; between 2.3% ('Involuntary psychoactive substance consumption') and 9.7% ('Intention to quit smoking') for the questions presenting the option DK in the CONS domain; and between 1.2% ('Child record health booklet') and 14.1% ('Complementary insurance') in the questions presenting the option DK of the ADM domain.

Class 2 (Partial Item Nonrespondents for options DK in FAM and NS in MHM) comprised 11.8% of students using the DK option in the questions belonging to the FAM domain. In particular, the questions 'Father's disease episodes' and 'Mother's disease episodes' accounted for 88.5% and 84.4% respectively. The percentages were between13.2% ('Migraine – light or noise') and 28.9% ('Migraine – side of the head') for the questions presenting the option NS within the MHM domain.

Class 3 (Item Nonrespondents for options DK in ADM and NS in MHM) included 10.4% of students. In particular, among the questions presenting the option DK within the ADM domain, the highest percentage was of 89.7 for the question 'Vaccination of Measles-Mumps-Rubella'. As for the use of the option NS across questions in the MHM domain, percentages ranged from 11.5% ('Migraine – nausea') to 23.1% ('Migraine – side of the head').

Class 4 (Medium Item Nonrespondents for option DWA) comprised 6.8% of students who used the DWA option across all domains. The highest percentages were 61.4% in the FAM

Table 3. Class proportions and probabilities of item nonresponse by option and question domain.

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
6 classes solution*	64.2%	11.7%	10.4%	6.8%	5.5%	1.5%
Family						
DK						
Father's disease episodes	0.064	**0.885**	0.233	0.089	0.675	0.276
Mother's disease episodes	0.034	**0.844**	0.189	0.077	0.299	0.221
Siblings' handedness	0.106	0.212	0.202	0.196	0.397	**0.534**
Parents' handedness	0.015	0.057	0.049	0.023	**0.5**	0.319
Family education levels	0.019	0.058	0.073	0.076	**0.372**	0.241
Father is alive, age	0.002	0.008	0.006	0.008	**0.804**	0.635
Reason of mother's death	0.032	**0.123**	0	0	0	0
Reason of siblings' death	0.054	0.073	0	0	**0.124**	0
Reason of father's death	0	0.075	0	0.037	**0.093**	0
Mother is alive, age	0	0.006	0.001	0.003	0.313	**0.528**
DWA						
Reason of siblings' death	0	0	0	0.614	0	**1**
Divorced/separated parents	0.01	0.043	0.007	0.077	0.136	**0.426**
Father's disease episodes	0.001	0.01	0.006	0.2	0.023	**0.557**
Reason of mother's death	0	0	0	**0.229**	0.065	0
Mother's disease episodes	0.001	0.011	0.005	0.193	0.011	**0.56**
Reason of father's death	0	0.022	0.047	0.06	0	**0.205**
Family support	0.003	0.023	0.022	0.051	0.038	**0.296**
Presence of siblings	0.003	0.011	0.009	0.028	0.03	**0.334**
Living place during childhood	0	0.004	0	0.008	0.005	**0.15**
Mother is alive	0	0	0	0.007	0	**0.201**
Father is alive	0	0	0.001	0.021	0.021	**0.264**
Mental Health & Migraine						
DWA						
Suicidal thoughts or attempts	0.027	0.081	0.05	0.155	0.1	**0.274**
Consulting a psychiatrist	0.005	0.013	0.017	0.042	0.019	**0.166**
NS						
Migraine – side of the head	0.143	0.289	0.231	0.21	0.167	**0.307**
Migraine – aggravated	0.132	**0.283**	0.189	0.257	0.12	0.234
Migraine – pulsatile	0.106	**0.211**	0.175	0.146	0.136	0.173
Migraine – nausea	0.069	0.166	0.115	0.104	0.081	**0.278**
Migraine – very strong	0.067	0.137	0.118	0.074	**0.135**	0.134
Migraine – light or noise	0.066	0.132	0.160	0.074	0.065	**0.202**
Sexual Life						
DWA						
Age first sexual intercourse	0.014	0.031	0.032	**0.375**	0.08	0.171
Number of female/male partners	0.008	0.042	0.026	**0.374**	0.043	0.171
Sexual intercourses	0.019	0.031	0.026	0.163	0.034	**0.332**
Emergency contraception**	0.001	0.004	0.005	0.07	0	**0.285**
Abortion**	0.001	0.005	0	0.046	0	**0.236**
Consumptions						
DK						
Intention to quit smoking	0.097	0.15	0.169	0.139	0.133	**0.316**
Involuntary psychoactive substance consumption	0.023	0.061	0.036	0.052	0.036	**0.082**
DWA						
Other drugs consumption	0.012	0.04	0.062	0.33	0.131	**0.419**
Lifetime cannabis consumption	0.005	0.015	0.01	0.071	0.007	**0.193**
Lifetime psychoactive substances use	0.002	0.009	0.001	0.043	0.004	**0.192**
Type of psychoactive substances	0	0.008	0.003	0.027	0.007	**0.176**
Recent cannabis consumption	0.002	0.002	0.008	**0.05**	0	0.042
Hurt because of alcohol	0.001	0.012	0.005	0	0	**0.026**
Involuntary psychoactive substance consumption	0	0	0.001	0.004	0	**0.079**
Health Administrative Issues						
DK						
Vaccination of Measles-Mumps-Rubella	0.082	0.185	**0.897**	0.109	0.258	0.382
Complementary insurance	0.141	0.235	0.316	0.278	0.219	**0.524**
Vaccination Hepatitis B	0.034	0.093	**0.75**	0.071	0.187	0.353

(*Continued*)

Table 3. (Continued).

6 classes solution*	Class 1 64.2%	Class 2 11.7%	Class 3 10.4%	Class 4 6.8%	Class 5 5.5%	Class 6 1.5%
Vaccination Papillomavirus**	0.049	0.093	**0.478**	0.119	0.161	0.352
Social insurance	0.048	0.081	0.125	0.126	0.115	**0.27**
Scholarship	0.034	0.042	0.08	0.114	0.058	**0.357**
Weight and height	0.031	0.039	0.073	0.093	0.118	**0.261**
Child health record booklet	0.012	0.031	0.073	0.033	0.054	**0.107**

The two highest probabilities are underlined in grey. The first highest probability is in bold.
* Class 1: High Item Respondents
Class 2: Partial Item Nonrespondents for options DK in FAM and NS in MHM
Class 3: Item Nonrespondents for options DK in ADM and NS in MHM
Class 4: Medium Item Nonrespondents for option DWA
Class 5: Item Nonrespondents for option DK in FAM
Class 6: High Item Nonrespondents
** Questions addressed only to female students

domain (question on 'Reason of siblings' death'), 15.5% in the MHM domain (question on 'Suicidal thoughts or attempts'), 37.5% in the SEXL domain (question on 'Age first sexual intercourse'), and 33.0% in the CONS domain (question on 'Other drugs consumption').

Class 5 (Item Nonrespondents for option DK in FAM) included 5.5% of students who used the option DK in the FAM domain. The highest probability of using the DK option was 80.4% corresponding to the question 'Father is alive, age').

Finally, class 6 (High Item Nonrespondents) was composed of 1.5% of students who were estimated to have a high probability of nonresponse, regardless of question domain and specific nonresponse option offered. In particular, students of this class used the option DWA with a higher mean probability in all domains presenting this option (FAM, MHM, SEXL and CONS). They also presented very high mean probabilities in all other domains for NS (22.1%) and DK (28.8%) options. The highest percentages were 56.0% in the FAM domain (DWA option used in the question 'Mother's disease episodes'), 30.7% in the MHM domain (NS option used in the question 'Migraine – side of the head'), 33.2% in the SEXL domain (DWA option used in the question 'Sexual intercourses'), 41.9% in the CONS domain (DWA option used in the question 'Other drugs consumption'), and 52.4% in the ADM domain (DK option used in the question 'Complementary insurance').

Relationship between the latent variable with six classes and gender, age and field of study

Table 4 shows the percentages of female students, age and field of study categories in each class. The relationship between the three variables and the classes was highly significant ($p = 0.000$). Looking at extreme classes, i.e. class 1 (High Item Respondents) and class 6 (High Item Non respondents), students belonging to class 1 were more female, aged 22–30 years old and studying medicine. Students belonging to class 6 were more male, aged 18–20 years old and studying Humanities and Letters.

Table 5 presents the results of the multinomial multivariate regression model. The three covariates were significantly associated with the classes. As for gender, the use of nonresponse options by male students was higher in classes 3, 5 and 6. Concerning the variable age, almost all ORs were inferior to 1, which means that as the age increased, the probability of using non-response options decreased. Finally, the fields of study related to health (Life Sciences and Medicine) were protective factors for the use of nonresponse options in any question domain, with respect to Humanities and Letters students.

Table 4. Relationship between the latent variable with 6 classes and gender, age and field of study.

6 classes solution*	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	p
Gender (N = 8,663)							
(Male)	65,6%	9,3%	12,2%	5,1%	5,8%	1,9%	p = 0.000
(Female)	68,7%	10,9%	9,0%	5,2%	5,0%	1,2%	
Age (N = 8,663)							
(18–20)	65,0%	11,0%	11,4%	5,9%	5,1%	1,6%	p = 0.000
(20–22)	71,2%	9,8%	8,0%	5,0%	4,7%	1,2%	
(22–24)	69,4%	11,7%	9,0%	3,3%	5,6%	1,1%	
(24–30)	69,8%	8,1%	8,5%	5,6%	6,9%	1,1%	
Field of study (N = 7,193)**							
Humanities and Letters	60,6%	10,9%	14,3%	5,4%	6,8%	2,1%	p = 0.000
Life Sciences	73,9%	9,9%	6,2%	5,8%	3,6%	0,5%	
Medicine	83,7%	6,9%	1,3%	4,4%	3,1%	0,6%	
Science Technology	62,1%	11,3%	13,2%	5,5%	6,5%	1,4%	
Law and Economy	59,2%	12,2%	14,2%	6,6%	5,8%	1,9%	
Other	65,4%	12,0%	10,7%	4,9%	6,0%	1,1%	

* Class 1: High Item Respondents
Class 2: Partial Item Nonrespondents for options DK in FAM and NS in MHM
Class 3: Item Nonrespondents for options DK in ADM and NS in MHM Class 4: Medium Item Nonrespondents for option DWA
Class 5: Item Nonrespondents for option DK in FAM
Class 6: High Item Nonrespondents
*The field of study contained 17.0% (n = 1,470) missing data due to technical problems, which were excluded from the analyses. To justify our choice, we also verified that the inclusion of the missing values in our analysis did not change significantly the OR in the multinomial model.

Table 5. Multinomial model assessing the associations between nonresponse classes and gender, age and field of study.

5 classes solution*	Class 2	Class 3	Class 4	Class 5	Class 6
Gender					
OR (Male)	0.948	1.616****	1.105	1.389***	1.979***
Age					
OR [20–22)	.868	.658	.775**	.834	.694
OR [22–24)	1.061	.725	.507****	1.003	.477**
OR [24–30]	.764	.703	.950	1.178	.530
Field Study					
Law and Economy	1.140	.969	1.249	.861	.896
Science Technology	1.040	.874	1.016	.893	.626
Life Sciences	.740***	.329****	.842	.427****	.170****
Medicine	.473****	.066****	.610***	.313****	.211****
Other	1.028	.671***	.833	.807	.483**

Multivariate model adjusted on gender, age and field of study.
* Class 1: High Item Respondents
Class 2: Partial Item Nonrespondents for options DK in FAM and NS in MHM
Class 3: Item Nonrespondents for options DK in ADM and NS in MHM
Class 4: Medium Item Nonrespondents for option DWA
Class 5: Item Nonrespondents for option DK in FAM
Class 6: High Item Nonrespondents
$p < 0.05$;*$p < 0.01$, ****$p < 0.001$ according to the Wald statistic. Interactions were not statistically significant. Class 1 is reference in dependent variable. Female, [18–20) and Humanities and Letters are the reference categories in independent variables.

Discussion

Principal findings and comparison with previous studies

We presented a study on item nonresponse in an online survey on University students' health using LCA. The application of this methodology allowed us to illustrate how nonresponse options can provide valuable information in an online health survey by taking into account simultaneously both survey's contextual characteristics (nonresponse options and question domains) and nonrespondents' individual characteristics (age, gender and field of study). Our analysis approach was based on previous research (Feick, 1989; Shoemaker et al., 2002) suggesting that item nonresponse can be influenced by the survey's contextual characteristics and the (non)respondents' individual characteristics.

Through a first descriptive analysis, we observed that the highest rates of item nonresponse were in the Family and the Health Administrative Issues domains, with the questions on parents' disease episodes, presence of vaccination and possession of a complementary insurance reporting the highest rates of use of nonresponse options. This was in accordance with Feick's findings (1989) reporting very high item nonresponse for questions on remote topics like family medical history. We also observed that item nonresponse was higher for knowledge-related questions compared to sensitive ones.

Concerning the nonresponse options, DK was by far the most used option, followed, in order, by NS and DWA. There are legitimate reasons for this higher use of the DK option concerning knowledge-related questions: students might not have opinions on all issues or truly ignore, for instance, their parents' disease episodes. High use of the DK option is also documented in other studies among youth (Denscombe, 2009; Heerwegh & Loosveldt, 2008). The use of the DWA option was limited revealing that students were prone to disclose information concerning their life in contrast with previous research in the general population (Joinson et al., 2008). The age might then explain such different attitude.

Then, we used LCA to check whether nonresponse options were used mostly or exclusively by the same participants, or whether the item nonresponse rates depended on the nonresponse options or the question domain or both. Only a small group of participants, i.e. High Item Nonrespondents, used all nonresponses options across all question domains. However, for Partial Item Respondents, the use of item nonresponse was different based on nonresponse options and question domains.

The patterns of nonresponse were associated with gender, age and field of study. In particular, the men-women differences in regard to nonresponse were noticeable. Our hypothesis was then confirmed: younger, male and non-health-related students reported the highest rates of DK, NS and DWA answers. These results were in line with those of a previous study (Porter & Whitcomb, 2005) reporting that survey response is greatest for females, but not with the study by Feick (1989) where more women used DK. Again, the specific characteristics and behaviours of the University student population may explain such differences.

Our study was conducted with the intent of identifying which domains in a questionnaire could present more nonresponse options and which type of respondent could use such nonresponse options. These information can help designing a questionnaire, as reported in previous studies (Durand & Lambert, 1988; Gilljam & Granberg, 1993; Groothuis & Whitehead, 2002; Shoemaker et al., 2002). Furthermore, the use of DK, DWA and NS is nonignorable, especially when accounting for one third of the sample (classes from 2 to 6 in our study) and might represent a prodromal sign of discomfort or ailment. Giving respondents the possibility to select DK, NS and DWA options could guarantee more realistic answers rather than false forced ones.

Limitations

There are some limitations to address. First, the nonresponse options were assigned by the authors of the questionnaire in pre-identified questions. The description of item nonresponse across nonresponse options and question domains may then be biased (research bias). This might be the case especially of the NS option, which was exclusively proposed for the migraine domain. However, the introduction of the DK, DWA and NS options was based on the results of a Delphi procedure including a pilot test of the questionnaire and of several focus groups. Second, three questions were addresses only to female students (emergency contraception, abortion, vaccination papillomavirus) thus potentially influencing the description of our classes. We also stratified our results by gender and observed that the distribution of the classes was not noticeably impacted. Finally, in this first study, we analysed only gender, age and field of study as covariates describing the individual characteristics of the (non)respondents. These three variables were used as an example of how to analyse and interpret the classes produced by the LCA methodology. Future studies might include other socio-demographic covariates in order to throw more light on correlates of item nonresponse. The choice of the socio-demographic covariates to take into account in the description of the classes would be instructed by the specific population under study (e.g. minority youth), as well as the research topic (e.g. religion, politics).

Strengths and implications

To the best of our knowledge, this study is among the first analysing through LCA item nonresponse in an online health survey addressed to young people. We showed the usefulness of LCA as a method to capture item nonresponse and describe its patterns. By examining the existence of different groups of respondents who have an unformed attitude on a topic or who are not willing to disclose their opinion across specific question domains, LCA allowed us to test the importance of including nonresponse options in our survey. One useful way to place LCA among other common latent variable models is to think of LCA as a way to group similar people together, whereas factor analysis groups items. The groups in LCA are unobserved (latent) and are based on the individuals' set of responses to the indicators. Thus, LCA can be thought of as a 'person-centred' approach to creating empirically derived typologies, contrasting the dominant 'variable-centred' tradition that generally requires arbitrary cut-offs for classifying or differentiating among individual cases (Nylund, Bellmore, Nishina, & Graham, 2007). Furthermore, strengths of our study include also the use of numerous data from a large online survey on students' health and lifestyle.

This study has several implications for future survey studies. Understanding the survey's contextual characteristics associated to item nonresponse may help identifying in which domains it is important to keep informative nonresponse options, and in which questions such options are less useful. The design of the questionnaire would then be improved so as to maximise the use of valuable item nonresponse rates, thus avoiding the random inclusion of DK, NS and DWA options.

On the other hand, once the group of higher item nonrespondents is identified, researchers can think of alternative ways to collect information from nonrespondents presenting similar characteristics by designing online questions differently based on the characteristics of this specific group (e.g. more direct wording or unambiguous plain phrasing).

Finally, we especially looked at the role of item nonresponse in online surveys in the health sector with a specific focus on young people. Our conclusions might be useful also for other topics and sectors covering sensitive and knowledge-related issues, e.g. politics, religion, environment. We believe the health sector is illustrative of the informative value of nonresponse options, but future studies are warranted to explore the appropriateness of the LCA methodology to analyse and describe item nonresponse patterns about these sensitive non-health-related issues (Tourangeau & Yan, 2007).

In conclusion, through our findings we underlined the importance of the methodological issues raised by item nonresponse and proposed LCA as the solution to handle such issues. LCA can provide more complete understanding on item nonresponse data and our study might further assist survey researchers with the design and implementation of online health surveys.

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