Health Information-Seeking Behaviors of a German Speaking Minority in Italy: Latent Class Analysis of a Population-Based Cross-Sectional Survey

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Research Article

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Abstract

Latent classes of health information-seeking behaviors of adults in a German-speaking minority of Italy were explored in a population-based, telephone survey on 10 health information sources conducted in South Tyrol, Italy. Data were collected from 504 adults (primary language German 68%, Italian 28%) and analyzed using latent class analysis and latent class multinomial logistic regression models. Three classes of health information-seeking behaviors emerged: “multidimensional” (23.3%), “interpersonal” (38.6%) and “technical/online” (38.1%). Compared to the “technical/online” class, “interpersonal” class members were older, had lower education than high school, and were less likely to be of Italian ethnicity. “Multidimensional” class members were more likely to be female, older, and of German ethnicity than those in the “technical/online” class. Linguistic ethnicity explains membership in classes of health-information-seeking behaviour. Policy makers and healthcare providers need to consider the health information-seeking behaviors of population subgroups to promote the health literacy skills of language minority groups.

Background

Although understanding health literacy in different populations is a growing area of research, little is known about ethnolinguistic aspects of health information-seeking behavior [1–3]. The social, cultural and linguistic context is an important co-determinant of health literacy and health information-seeking behaviour because it is critical for participation and empowerment [4–6]. Health literacy refers to an individual's “knowledge, motivation, and competences to access, understand, appraise and apply information to make decisions in terms of health care, disease prevention and health promotion” [7]. Information-seeking behaviour is crucial in the design of prevention education programmes [8–10]. Low health literacy is linked to poorer health outcomes [11]. The concept of health literacy has evolved from a focus on functional skills to a focus on higher order competencies such as seeking for and critical appraisal of health information and applying it in everyday life [12]. Today, people live in a flood of health-related information [13], and media literacy education can empower critical thinking to improve the use of media to obtain health information that aids healthy living [14].

Conceptual Framework

Although evidence suggests an increasing demand that disease prevention programs and health interventions be more culturally responsive [15], few published studies have focused on health information-seeking behaviors in the context of language minorities [16–18]. South Tyrol is an autonomous region in northern Italy (total population, 524.256 people), with 69% German- and 26% Italian-speaking individuals [19]. The two ethnolinguistic groups are being served by the same health care system and service providers , which impacts health literacy as a variable of interest [20].

The main objective of this study was to assess and describe health information-seeking behaviour in the South Tyrolean population. The aims were (1) to explore latent classes of health information-seeking behaviors and (2) to test the association between sociodemographic characteristics (i.e. age, gender, educational level, region of origin, and ethnolinguistic group) and latent class membership.

Methods

Data are derived from a population-based cross-sectional telephone survey study. Eligibility criteria for participants were living in South Tyrol, possessing a landline (only private households, no business phones), being at least 18 years old and being declared to either the German or Italian linguistic group. According to data from the National Statistics Institute (www.dati.istat.it) for 2015, from a total of 210,000 private households in South Tyrol, 122,000 (58%) had a landline and 208,000 (99%) of private households had at least one mobile phone; 92,000 (44%) solely used mobile phones. In the present study, only landline users were included since mobile phone users cannot be limited to South Tyrol. Interviews were conducted between August and September 2014 using computer-assisted telephone interviewing. Data collection was conducted by Apollis (www.apollis.it), which is a private research institution in Bolzano (BZ), Italy, conducting empirical studies for public and private clients with a focus on education, labor market topics, active aging and survey research. The goal was to conduct at least 500 interviews. A random sample of 1,445 households in South Tyrol with a landline number was contacted from professional interviewers. A total of 162 phone numbers were wrong, and 318 were not reachable at all. The remaining 965 were invited to participate in the telephone survey, and appointments for answering the phone survey were made: 458 did not participate in two of the second calls despite the appointment; for 46, no suitable appointment was found in the study period, 53 were not capable of participating, and 359 declined. Out of 507 phone interviews, three interviews were excluded from analyses, as participants were not eligible, which resulted in a total of 504 interviews. The interviews lasted from three to 28 minutes (mean = 12 minutes).

We assessed 10 common sources of health-related information: (1) being asked from others for advice (i.e., own knowledge), (2) magazines/newspapers, (3) TV/radio, (4) friends, (5) healthcare professionals, (6) courses, (7) medical literature, (8) random online search, (9) targeted online search in electronic databases and (10) online forums. These items were self-developed based on existing instruments and assessed on a 4-point Likert scale (ranging from 1 = never to 4 = often). Sociodemographic factors of participants included age (birth year), sex (male/female), mother language (German/Italian), educational level (highest degree), and region of origin (rural/urban).

Ethics

According to Italian law, approval by the Ethics Committee and written informed consent are not required in questionnaire-based and register-based population studies. The provision of information about the survey and its purpose, as well as voluntary participation at the telephone interview, provided implied consent. The study was performed in accordance with the Italian Personal Data Protection Law (Legislative Decree no. 196 of 30 June 2003) and was undertaken in accordance with the World Medical Association of Helsinki Declaration [21].

Statistical analysis

We used descriptive statistics, including means, standard deviations, frequencies, and cross-tabulations, to describe the health information-seeking behaviors, as well as the characteristics of the sample. To avoid biases, sampling weights based on the age and gender distributions for the population of South Tyrol according to the Provincial Statistics Institute for 2013 were employed for all analyses [19].

For the purpose of the analysis, health information indicators were dichotomized with 0 = “never”/”rarely” and 1 = “sometimes”/“often”. According to our research aims, we analyzed the data in two steps. First, we completed latent class analysis (LCA) to explore whether meaningful latent classes of peoples’ health information-seeking behaviors can be identified from the 10 dichotomous health information indicators. LCA is a statistical model used to identify underlying mutually exclusive and exhaustive subgroups of individuals with shared characteristics [22]. Because the number of latent classes is a priori unknown, a series of LC models with 1 to 5 latent classes were estimated. To avoid local maxima of log-likelihoods, 1000 random starts were used for each model. To select the appropriate number of classes, the Akaike Information Criterion (AIC) and the Bayes Information Criterion (BIC) were applied (lower values indicate better model fit). In addition, unadjusted and adjusted Lo-Mendell-Rubin (LMR) tests were used to evaluate whether the k class solution was superior to the k – 1 class solution. A significant LMR test suggests that the k class solution better fits the data than the k – 1 class solution. In addition to the statistical indices, the interpretability of the model coefficients was inspected for each model [23]. LCA assumes that underlying latent classes explain why observed indicators are related to each other (known as the local independence assumption). Standardized bivariate residuals were used to assess potential violations of the local independence assumption.

After latent class enumeration, a latent class multinomial logistic regression model was used to predict class memberships. Note that a two-step approach (in which modally assigned LC memberships are used as dependent variables in a multinomial logistic regression) is prone to overestimating the influence of predictors [24]. Thus, after deciding upon the optimal number of classes, a one-step approach was applied where class identification and LC membership prediction were performed simultaneously [25] based on respondents’ age (in years), gender (0 = male, 1 = female), education (0 = less than high school, 1 = high school +), region (0 = urban, 1 = rural), and ethnolinguistic group (0 = German, 1 = Italian). The level of significance was set at $P < 0.05$. Data analysis was conducted using Mplus version 7.3 [26]. Only four observations had missing values among the health information indicators. Full information maximum likelihood estimation (FIML) was applied to handle these missing data points. In addition, twenty subjects (4.0%) had missing values in (at least) one of the covariates. No significant differences in demographics and health-information seeking behavior were observed for this small subgroup, which was thus discarded from latent class multinomial logistic regressions leaving $n = 484$ subjects.

Results

Data were collected from 504 people, amounting to a response rate of 52% (nonresponse rate: 37%). The mean age was 48.9 years; 49% of the participants were male; and the primary language German 68%, Italian 28%. The sociodemographic characteristics of the respondents are summarized in Table 1.

Table 1
Descriptive statistics of weighted samples by ethnolinguistic group.

		Ethno-linguistic Group		
Variable		German	Italian	Total
Age (years)	*M* (*SD*)	47.9 (18.7)	51.1 (18.6)	48.9 (18.7)
Sex	*n* (%)			
Male		168 (49.1)	70 (49.6)	238 (49.3)
Female		174 (50.9)	71 (50.4)	245 (50.7)
Educational Level	*n* (%)			
less than high school		210 (61.2)	61 (43.3)	271 (56.0)
high school +		133 (38.8)	80 (56.7)	213 (44.0)
Region	*n* (%)			
urban		80 (23.3)	115 (81.6)	195 (40.3)
rural		263 (76.7)	26 (18.4)	289 (59.7)
Source of Information				
Beeing asked for advice	*n* (%)			
never/rarely		166 (48.5)	66 (46.8)	232 (48.0)
sometimes/often		176 (51.5)	75 (53.2)	251 (52.0)
Newspaper/Magazines	*n* (%)			
never/rarely		105 (30.7)	44 (31.2)	149 (30.8)
sometimes/often		237 (69.3)	97 (68.8)	334 (69.2)
TV/Radio	*n* (%)			
never/rarely		107 (31.2)	63 (44.7)	170 (35.1)
sometimes/often		236 (68.8)	78 (55.3)	314 (64.9)
Friends	*n* (%)			
never/rarely		99 (28.9)	57 (40.1)	156 (32.2)
sometimes/often		244 (71.1)	85 (59.9)	329 (67.8)
Professionals	*n* (%)			
never/rarely		181 (52.9)	59 (42.8)	240 (50.0)

		Ethno-linguistic Group		
sometimes/often		161 (47.1)	79 (57.2)	240 (50.0)
Courses	*n* (%)			
never/rarely		272 (79.3)	119 (83.8)	391 (80.6)
sometimes/often		71 (20.7)	23 (16.2)	94 (19.4)
Medical Literature	*n* (%)			
never/rarely		227 (66.2)	102 (72.3)	329 (68.0)
sometimes/often		116 (33.8)	39 (27.7)	155 (32.0)
Random Online Search	*n* (%)			
never/rarely		194 (56.6)	68 (47.9)	262 (54.0)
sometimes/often		149 (43.4)	74 (52.1)	223 (46.0)
Targeted Online Search	*n* (%)			
never/rarely		198 (57.7)	87 (61.7)	285 (58.9)
sometimes/often		145 (42.3)	54 (38.3)	199 (41.1)
Online Forums	*n* (%)			
never/rarely		327 (95.6)	131 (92.9)	458 (94.8)
sometimes/often		15 (4.4)	10 (7.1)	25 (5.2)
Note: *n* = frequencies, *M* = mean, *SD* = standard deviation				

From the 10 health-information seeking behaviors (see Table 1), the three most frequent behaviors were seeking information in “Newspapers/Magazines” (69.2%), from “Friends” (67.8%), and in “Radio/TV” (64.9%). The three less frequent health-information seeking behaviors were “Online Forums” (5.2%), “Courses” (19.4%), and “Medical Literature” (32.0%).

Table 2 summarizes the LC model fit indices and estimated class sizes (based on modal assignment) for k = 1–5 latent classes. For reasons of comparison, LC models were estimated with and without sampling weights. In general, AIC values decrease with every additional class, which hampers distinct model selection. Because this is also in line with the observation that the AIC may tend to overestimate the number of latent classes, we primarily focused on the BIC. For both weighted and unweighted LC models, the BIC favored the 3-class solution. Adjusted and unadjusted LMR tests also favored the 3-class solution when no sampling weights were used and suggested a 2-class solution when sampling weights were incorporated. Differences in parameter estimates obtained from the weighted and unweighted 3-class models were modest, and the weighted 3-class model showed an acceptable model fit ($\chi 2(991) = 973.48$, $p = .648$). Thus, overall, we decided to retain the weighted 3-class solution as the final model. Note that this model showed one significant standardized bivariate residual involving the health information sources newspapers/magazines and TV/radio. To account for this association, the final model was re-estimated, allowing this residual covariance.

Table 2
Summary of latent class model fit with and without sampling weights (indices suggesting best model fit are marked bold)

					Latent class sizes based on modal assignment				
No. of classes	AIC	BIC	LMR	adj. LMR	LC1	LC2	LC3	LC4	LC5
Without sampling weights									
1	5918.6	5960.8	-	-	504	-	-	-	-
2	5656.4	5745.1	< .0001	< .0001	182	322	-	-	-
3	5587.0	**5722.1**	**0.010**	**0.011**	156	107	241	-	-
4	5554.8	5736.4	0.213	0.219	136	111	206	51	-
5	**5539.8**	5767.9	0.603	0.607	85	144	62	64	149
With sampling weights									
1	6041.1	6083.3	-	-	504	-	-	-	-
2	5836.2	5924.9	**< .001**	**< .001**	222	282	-	-	-
3	5771.9	**5907.0**	0.203	0.209	197	103	204	-	-
4	5736.3	5917.9	0.749	0.749	127	125	142	110	-
5	**5714.7**	5942.7	0.742	0.743	86	122	58	106	131
Note: AIC = Akaike Information Criterion, BIC = Bayes Information Criterion, LMR = *p*-value of the Lo-Mendel-Rubin test, adj. LMR = *p*-value of the adjusted LMR.									

LC-specific patterns of heath information-seeking behaviors are summarized in Fig. 1 and can be described as either “multidimensional-”, “interpersonal-”, or “technical/online”. Members of the “multidimensional” group (23.3%) reported performing almost all behaviors of seeking health information, ranging from exchange with friends, health professionals or other human sources to use of medical literature and electronic databases or the internet. The “interpersonal” group (38.6%) was more likely to seek information from friends or health professionals, while the “technical/online” group (38.1%) was more likely to use random or targeted online searches in electronic databases or the internet.

In the next step, covariates were entered into the LC model to predict latent class memberships. Descriptive characteristics for the three latent classes are summarized in Table 3. In addition to testing the main effects on class memberships, all potential two-way interactions were investigated [27]. Nonsignificant predictors were omitted from the model for reasons of parsimony. Findings from the latent class multinomial logistic regressions are summarized in Table 4. No significant differences were observed for urban/rural regions. Similarly, all two-way interactions were nonsignificant. Compared to the “technical/online” group, members of the “multidimensional” group were significantly more likely to be female, be older, and of German ethnicity. No difference was found for educational level. Members from the “interpersonal” group were significantly more likely to have higher age and education lower than high school and less likely to be of Italian ethnicity than those in the “technical/online” group. As displayed in Fig. 2, the probability of membership in the “technology/online” group decreases with age, whereby the probability of being a member in the “interpersonal” group increases with age. The probability of membership in the “multidimensional” group peaks at approximately 50 years of age and decreases with older age.

Table 3
Descriptive statistics of weighted sample by latent class membership.

		Latent Class Membership		
Variable		LC1: "technical/online"	LC2: "multidimensional"	LC3: "interpersonal"
Class Size	*n* (%)	184 (38.1)	113 (23.3)	187 (38.6)
Ethno-linguistic group	*n* (%)			
German		110 (32.1)	95 (27.7)	138 (40.2)
Italian		75 (53.2)	18 (12.8)	48 (34.0)
Sex	*n* (%)			
Male		109 (45.6)	31 (13.0)	99 (41.4)
Female		76 (31.0)	81 (33.1)	88 (35.9)
Educational Level	*n* (%)			
less than high school		76 (28.0)	40 (14.8)	155 (57.2)
highschool +		108 (50.7)	73 (34.3)	32 (15.0)
Region	*n* (%)			
rural		88 (45.1)	45 (23.1)	62 (31.8)
urban		96 (33.2)	68 (23.5)	125 (43.3)
Age (years)	*M* (*SD*)	35.8 (14.6)	46.9 (13.2)	62.9 (15.0)
Note: *M* = mean, *SD* = standard deviation				

Table 4
Latent class multinomial logistic regression of patterns of health information-seeking behaviors based on weighted sample.

	LC2: "multidimensional"			LC3: "interpersonal"		
		95% CI			95% CI	
Variables	OR	lower	upper	OR	lower	upper
Sex: Female	3.41	1.06	10.97	0.90	0.26	3.09
Age (in years)[(a)]	1.06	1.02	1.10	1.13	1.09	1.18
Ethno-linguistic group: Italian	0.18	0.05	0.70	0.27	0.09	0.84
Educational Level: High school +	1.75	0.58	5.25	0.21	0.08	0.60
Reference Class: LC1: "technical/online"						
(a) mean centered						

Discussion

In this study, patterns in health information-seeking behaviors in the adult population of South Tyrol revealed three health information-seeking groups in LCA, namely, “interpersonal”, “technical/online”, and “multidimensional”. LCA is increasingly used in health literacy and prevention research [28–30]. While the “multidimensional” group of adults performed almost all behaviors of seeking health information, ranging from exchange with friends, health professionals or other human sources to use of medical literature, electronic databases and the internet, the “interpersonal” group sought information mainly from friends and/or health professionals. The “technical/online” group used random or targeted online searches in electronic databases or the internet. Class membership was explained by age, sex, level of education and ethnicity. Health information-seeking behaviors differed significantly between the two linguistic groups.

In regions with culturally and linguistically diverse backgrounds, differences in people’s behavior in searching for health-related information have been described previously [31]. Language minorities may well impact health literacy in South Tyrol; for instance, drug package inserts are provided in Italian language only. In contrast to nonmedical public services established in South Tyrol for both German and Italian ethnic groups, there is a single public health care system for the entire population. Although language skills of the German-speaking minority in Italian have not been assessed in this study, only part of the population is known to be sufficiently bilingual.

Previous studies revealed that health literacy depends on a variety of factors and barriers, including language [32], social group history [33], patterns related to access and usage of digital technologies [34, 35], frequency of watching health-related television [36, 37], and involvement in social networks [38, 39]. Difficulties related to understanding health information and engaging with healthcare providers go hand in hand [12]. Reliance on internet-based technologies to disseminate health information and services is well known and has most recently been exemplified in the coronavirus pandemic [40–42].

Access to health information is at a particular risk, as there is a particular shortage in German-speaking health care professionals in South Tyrol, which has become a general healthcare problem in Italy today [43]. In our study, friends and healthcare professionals were two particularly important sources for providing health-related information for the German-speaking population in the “interpersonal” and the “multidimensional” LCA groups. Moreover, health professionals often have a limited understanding of health literacy levels, including health-seeking behaviors and the consequences of low health literacy for their patients [44].

Providing health-related information to adults in the “interpersonal” and the “multidimensional” groups is particularly language-dependent. Healthcare professionals need to assess the health literacy level as well as effectively communicate and consider health literacy, among other patient characteristics, when selecting patients for care management programs [35]. Health policy makers and healthcare organizations should implement interventions not only to develop health information-seeking skills in populations they serve but also to prepare healthcare professionals, e.g., general practitioners and family nurses, for better provision of information and materials that are easily accessible and understandable [35]. Critical pedagogy applied to in-service education has been shown to effectively stimulate professionals' awareness of their potential to change their practice and work environment towards improved health literacy in special linguistic contexts [18].

One-third of adults in the general South Tyrolean population reported primarily seeking health information through random or targeted online searches in electronic databases or the internet. Our study revealed that being Italian-speaking, male sex, being younger (< 50 years) and having higher education increased the likelihood of applying this health information-seeking behaviour. In Germany, middle and high socioeconomic status, female sex, being married or living in a stable relationship and heavy use of health-care services favor the use of the internet for health-related information [45]. As online information offers great potential to empower the population, efforts made in the South Tyrol healthcare system to improve access to online health information (e.g., eHealth services) may focus on individuals from the “interpersonal” group to enhance their capacity to use it effectively through educational programs [13].

Several limitations of this study must be taken into consideration. First, the study database is representative of the adult population (> 18 years) living in private households and using a land line phone in South Tyrol in 2014. Health literacy and health information-seeking behaviors from children and adolescents have not been investigated [46, 47]. Second, with this study, we investigated only individual health information-seeking behavior. There are still few data on public health literacy, which is defined as the degree to which individuals and groups can obtain, process, understand, evaluate, and act on information needed to make public health decisions that benefit the community [48]. Thus, the impact this study may have on prevention science and public health decisions in South Tyrol is uncertain. Third, social media, which are increasingly used for the dissemination of health-related information [49], was not investigated in this study. Fourth, in our sample, the use of the internet as a valuable source of health-related information was low in both linguistic groups, which may have changed today as the survey was already performed in 2014.

In conclusion, we identified three groups of health information-seeking behaviors in the adult South Tyrolean population, i.e., “multidimensional”, “interpersonal” and “technical/online”. In addition to age, sex, level of education, minority language explained group membership. Compared to the “technical/online” group, members from the “interpersonal” group were significantly more likely to have higher age, education lower than high school and less likely to be of Italian ethnicity. Members of the “multidimensional” group were significantly more likely to be female, to have higher age, and to be of German ethnicity than those in the “technical/online” group.

New Contribution To The Literature

This analysis provides insight into how and where a language minority in Italy obtains health information. Policy makers and healthcare providers need to consider the information-seeking behaviors of language minority subgroups to tailor communication strategies and promote health literacy skills.

Declarations

Conflict of Interest Declaration

All authors have disclosed that they do not have any potential conflicts of interest.

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Figures

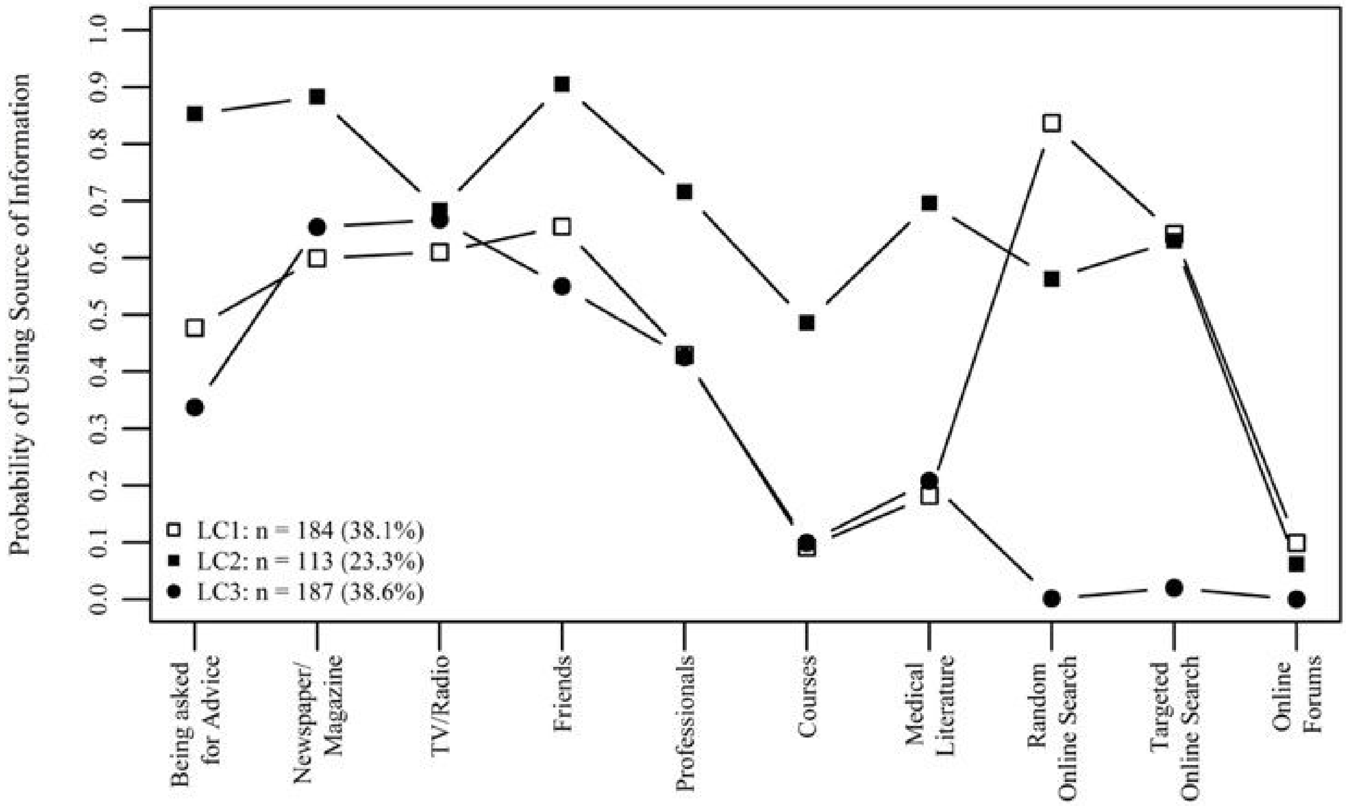

Figure 1

Sources of health information of different latent classes of information-seeking groups. LC1, “technology/online” pattern; LC2, “multidimensional” pattern; LC3, “interpersonal” pattern (based on weighted sample).

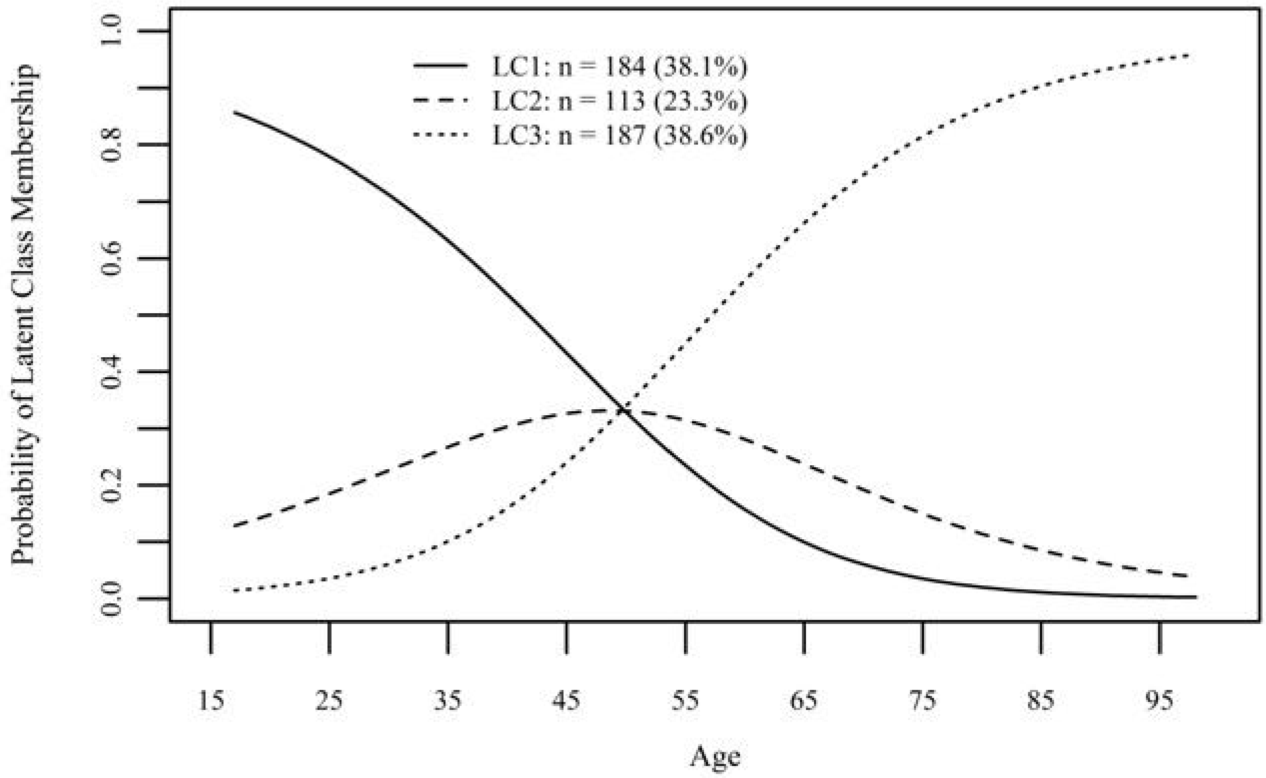

Figure 2

Age distribution of three different latent class analysis health information-seeking groups. LC1, “technology/online” pattern; LC2, “multidimensional” pattern; LC3, “interpersonal” pattern (based on weighted sample).