3. METHOD

This study is part of a larger project “Risk Appraisal and Consequences in Korea” supported by the German Research Foundation. The participants took part in questionnaire study with two measurement points and an average interval of six months. The first part of this section provides a description of the recruitment procedures and demographic characteristics of participants. In the second part a description of measures being used will be given. The last section provides a general overview of the statistical methods employed to test the central hypotheses of the present study.

3.1 SAMPLE

3.1.1 Recruitment and Procedure

Residents of Seoul and Kyungki-do, South Korea were invited to participate in a public health screening. Volunteers were recruited from different location such as universities, institutions for the elderly, clerical institutions and police departments. Participants were examined by medical staff (height, weight, systolic and diastolic blood pressure, total cholesterol), and they received a detailed questionnaire that included items assessing social-cognitive variables and health behaviors along with pre-stamped return envelopes. Participants were instructed to fill out the questionnaire at home and to send it back within two weeks. Six months later participants were approached for the second time and were asked to complete the second questionnaire following the same procedure as the first time.

3.1.2 Participants

Table 3 gives an overview of the social-demographic characteristics of the total sample for the sub-samples of young and older adults. Overall, 1359 participants took part in the first wave of the study. The full sample comprised of individuals aged between 16 and 90 years (M = 33.7; SD = 16.3), 725 of whom were women and 611 were men.

As discussed earlier (see Chapter 2.3.3) the cut-off for middle age was set by 35 years (see also Lachman & James, 1997; Spiro, 1999). The middle aged and old aged groups were collapsed into one group of older adults. There was significant difference in the sex distribution between young and older adults age groups (χ^2 (1) =

51.27, $p < .001$). The sub-sample of older adults was predominantly female (68.4%), whereas the young adults sub-sample had a quite equal sex distribution (52.5% female).

There were differences in educational, occupational and marital status as well as difference in income between sub-samples of young and older adults (see Table 3). The younger sub-sample had a higher educational status than the older sub-sample. At wave1, 43.3% of the younger versus 23.7% of the older participants were graduates of the higher educational program. Further, the majority of the younger participants (54.0%) by the time of the survey were students, whereas the majority of the older participants were housewives (40.1%). The vast majority of younger participants were single (84.4%), whereas 75.9% of the older participants were married. The income distribution was slightly different between the two age groups (χ^2 (3) = 25.58, $p <$ .001), with 35.3% of older participants and 30.6% of younger participants in the highest income category.

Overall, 662 (48.7%) participants dropped out of the study by the second wave. As can also be seen in Table 3 the continuer sample (M = 32.1) was younger than the drop-out sample (M = 35.4) and this difference was significant $t(1344)$ = 3.64, $p < .01$). Regarding gender distributions, continuers and drop-outs did not differ significantly (χ^2 (1) = 1.00, n.s.). When comparing the continuers with the drop-outs significant differences in the distribution of educational (χ^2 (6) = 21.81, $p < .01$), occupational (χ^2 (9) = 40.70, $p < .001$), and marital (χ^2 (4) = 18.66, $p < .01$) status as well as income (χ^2 (3) = 24.70, $p < .001$) became apparent. Thus, the drop-out subsample was better educated, consisted of more housewives and less blue collar workers, were more likely to be in the highest income category and more likely to be married.

Table 3: Socio-demographic characteristics of participants

	Wave1			Wave2			
	Total (N = 1359)	Young adults (*n* = 910)	Older adults (*n* = 436)	Total (N = 697)	Young adults (*n* = 489)	Older adults (*n* = 202)	Drop-out (*n* = 662)
Age							
Mean (SD)	33.7 (16.3)	24.0 (5.1)	54.0 (12.5)	32.1 (17.1)	22.6 (5.0)	55.2 (13.6)	35.4 (15.3)
Sex							
Men	611 (45.7)	474 (52.5)	137 (31.6)	314 (47.1)	255 (54.1)	59 (30.1)	291 (44.2)
Women	725 (54.3)	429 (47.5)	296 (68.4)	353 (52.9)	216 (45.9)	137 (69.9)	368 (55.8)
		$\chi2$ (1) = 51.27, p < .0012			$\chi2$ (1) = 32.10, p < .001		
Education (%):							
No degree	10 (0.9)	4 (0.5)	6 (1.8)	8 (1.3)	0 (0.0)	8 (4.6)	3 (0.6)
Middle school	40 (3.7)	1 (0.1)	39 (11.7)	32 (5.2)	1 (3.1)	31 (17.9)	22 (4.4)
Dropped out of vocational training	34 (3.2)	2 (0.3)	32 (9.6)	40 (6.5)	18 (4.1)	22 (12.7)	17 (3.4)
High school degree or college dropout	424 (39.3)	289 (38.8)	135 (40.4)	242 (39.3)	177 (40.0)	65 (37.6)	172 (34.3)
Technical school	124 (11.5)	105 (14.1)	19 (5.7)	86 (14.0)	73 (16.5)	13 (7.5)	48 (9.6)
College or university	401 (37.2)	322 (43.3)	79 (23.7)	190 (30.9)	164 (37.1)	26 (15.0)	211 (42.1)
Graduate school or more	45 (4.2)	21 (2.8)	24 (7.2)	17 (2.8)	9 (2.0)	8 (4.6)	28 (5.6)
		$\chi2$ (6) = 198.83, *p* < .001			$\chi2$ (6) = 139.55, *p* < .001		
Occupation: (%)							
Student	418 (37.6)	415 (54.0)	3 (0.9)	210 (33.1)	208 (46.0)	2 (1.1)	182 (35.5)
Housewife	181 (16.3)	44 (5.7)	137 (40.1)	90 (14.2)	24 (26.7)	66 (36.1)	109 (21.3)
Unemployed	51 (4.6)	12 (1.6)	39 (11.4)	37 (5.8)	6 (1.3)	31 (16.9)	23 (4.5)
Blue collar worker	65 (5.9)	26 (3.4)	39 (11.4)	59 (9.3)	25 (5.5)	34 (18.6)	20 (3.9)
Skilled worker	30 (2.7)	17 (2.2)	13 (3.8)	17 (2.7)	13 (2.9)	4 (2.2.)	18 (3.5.)
Service or sales	57 (5.1)	23 (3.0)	34 (9.9)	43 (6.8)	30 (6.6)	13 (7.1)	26 (5.1)
White collar	65 (5.9)	43 (5.6)	22 (6.4)	33 (5.2)	22 (4.9)	11 (6.0)	36 (7.0)
Manager or entrepreneur	22 (2.0)	5 (0.7)	17 (5.0)	6 (0.9)	0 (0.0)	6 (3.3)	14 (2.7)
Professional freelancer	69 (6.2)	36 (4.7)	33 (9.6)	29 (4.6)	14 (3.1)	15 (8.2)	34 (6.6)
Other	153 (13.8)	148 (19.2)	5 (1.5)	111 (17.5)	110 (24.3)	1 (0.5)	50 (9.8)
		$\chi2$ (9) = 535.53, *p* < .001			$\chi2$ (9) = 309.81, *p* < .001		
Income (%)[1]							
<500 yen	68 (6.4)	32 (4.3)	36 (11.0)	54 (8.9)	26 (6.0)	28 (16.6)	22 (4.5)
510-1500 yen	171 (16.1)	116 (15.7)	55 (16.9)	117 (19.4)	73 (16.8)	44 (26.0)	74 (15.0)
1510-3000 yen	485 (45.5)	365 (49.4)	120 (46.8)	275 (45.5)	220 (50.6)	55 (32.5)	203 (41.2)
>3010	341 (32.0)	226 (30.6)	115 (35.3)	158 (26.2)	116 (26.7)	42 (24.9)	194 (39.4)
		$\chi2$ (3) = 25.58, *p* < .001			$\chi2$ (3) = 29.49, *p* < .001		
Marital status (%)							
Single	648 (60.1)	635 (84.4)	13 (4.0)	382 (62.5)	374 (84.4)	9 (5.3)	272 (54.6)
Married	351 (32.7)	106 (14.1)	245 (75.9)	183 (30.0)	61 (13.8)	61 (13.8)	192 (38.6)
Widowed	51 (4.9)	3 (0.4)	48 (14.9)	38 (6.2)	4 (0.9)	4 (0.9)	19 (3.8)
Remarried	10 (0.9)	4 (0.5)	6 (1.9)	3 (0.5)	1 (0.2)	1 (0.2)	6 (1.2)
Divorced	15 (1.4)	4 (0.5)	11 (3.4)	5 (0.8)	3 (0.7)	3 (0.7)	9 (1.8)
		$\chi2$ (4) = 623.57, *p* < .001			$\chi2$ (4) = 336.62, *p* < .001		

Note: [1]In thousand yen. [2] $\chi2$ tests pertain to differences between young and older adults age groups.

3.2 MEASURES

In the following section the measures used in the study are introduced. All scales were assessed at both measurement occasions. All scales were translated from German into Korean by native-language speakers and verified through back-translations (Behling & Law, 2000). They were then tested in a pilot study with respect to ambiguity, plausibility, and difficulty in order to reduce the frequency of invalid responses (cf. L. A. Clark & Watson, 1995). For the exact wording of the measurement instruments see Appendix D.

3.2.1 Health Behaviors

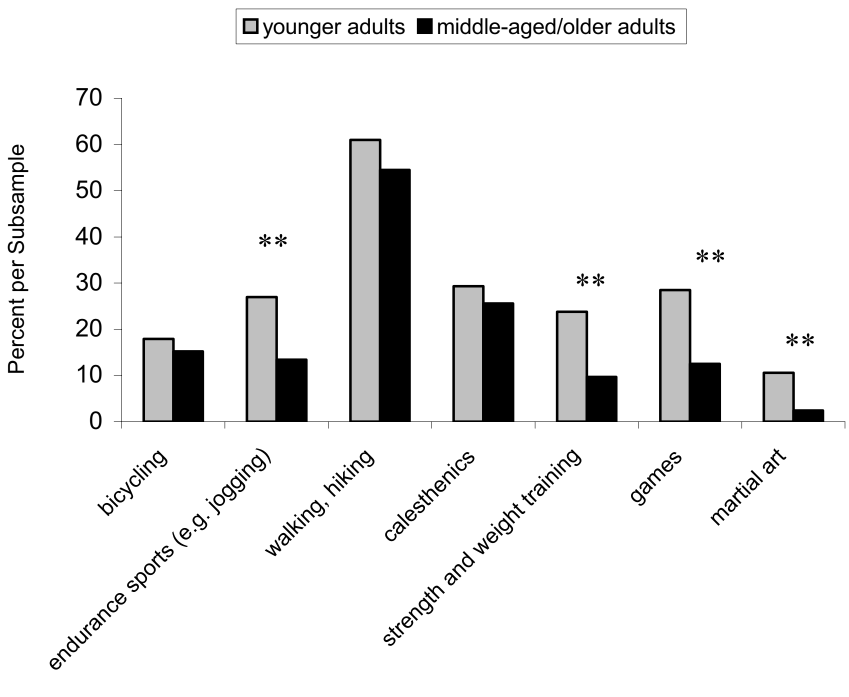
3.2.1.1 Nutrition

Evidence exists that a diet consisting of daily intake of fruits and vegetables and limited consumption of foods high in saturated fat can have beneficial effects on long-term health (Conner & Armitage, 2002; Willett, 1994). Self-reported nutrition behavior was assessed using the nutrition style scale developed by Renner, Hahn, and Schwarzer (1996). The nutrition style scale was developed as a brief dietary assessment tool that targets a general optimal diet for prevention of common chronic diseases of adulthood. There were two dimension of nutrition behavior, one related to a high-fiber dietary intake, with five items (Cronbachs's $\alpha = .68$ at T1 and $\alpha = .72$ at T2) and the other related to a low-fat dietary intake, with nine items (Cronbachs's $\alpha = .79$ at T1 and $\alpha = .79$ at T2). Responses were made on four point scales ranging from 1 (not at all true) to 4 (exactly true).

3.2.1.2 Physical Activity

For the assessment of physical activity, participants were asked in line with the South Korean National Survey of Sport Participation (cf. M. Kim, 1996) and the EPIC-Norfolk Physical Activity Questionnaire (Wareham, Jakes, Rennie, Mitchell, Hennings, & Day, 2002), how often they engaged in different types of physical activity covering a broad range of aerobic, calisthenics, and resistance activities that are relevant for younger and older adults (see also Netz, Wu, Becker, & Tenenbaum, 2005). In particular, participants were asked how often they engage on average in a) cycling; b) endurance activities (jogging, running, swimming, rowing, etc.); c) walking, hiking; d) calisthenics, gymnastics, aerobics, dancing; e) strength and weight training; f) games (baseball, soccer, volleyball, tennis, squash, etc.); g) martial arts (karate, judo, taekwondo, aikido, kendo, kickboxing, etc.). The answers were given on a five-point Likert-type scale with 1 (*almost every day*), 2 (*3-4 times a week*), 3 (*once a week*), 4 (*1-3 times a month*) and 5 (*less than once a month or never*). Responses were recorded for every activity respectively into 0 (*never*), 0.5 (*1-3 times a month*), 1.0 (*once a week*), 2.5 (*2-3 times a week*), and 5 (*almost every day*). Afterwards, recorded responses were collapsed into a total sum score of physical activity per week. Moreover, engagement in physical activities was also assessed in a dichotomous way by asking respondents whether they are physically active on a regular basis.

As can be seen in Figure 2, participants reported different kinds of physical activities. Younger adults were more likely to be involved in endurance sports ($\chi^2(1) = 9.8$, $p < .01$), strengths and weight training ($\chi^2(1) = 11.6$, $p < .01$), games ($\chi^2(1) = 13.4$, $p < .001$) and martial arts ($\chi^2(1) = 8.1$, $p < .01$).



Note. More than one kind of physical activities possible. Percentages do not add to 100.

Figure 2: Descriptive statistics for physical activities of younger and middle aged/older adults

3.2.1.3 Alcohol Consumption

In order to assess alcohol consumption, respondents were first asked if they consume alcohol on a regular basis. In a second step, a typical quantity-frequency assessment of alcohol consumption was undertaken (cf. Alanko, 1984; Room, 1990). The quantity-frequency (QF) assessment of alcohol consumption consisted of three dimensions of quantity, frequency and variability. The accuracy of measurement is improved when beverage-specific questions are included (Rehm, 1998). First, the participants had to indicate how often they drink different alcoholic beverages, e.g. beer, wine, suju or spirits. The answers were given on a six point Likert-type scale with 1 (*daily*), 2 (*couple of times a week*), 3 (*once a week*), 4 (*1-3 times a month*), 5 (*very seldom*), and 6 (*never*). Responses were recorded for every beverage respectively into 0 (*never*), 0.1 (*very seldom*), 0.5 (*1-3 times a month*), 1 (*once a week*), 3 (*couple of times a week*) and 7 (*daily*). In the second step, participants were asked to indicate the amount (number of glasses) of the consumed alcohol on one occasion. The number of glasses per occasion was converted into gram ethanol (WHO, 2001). In the last step, the frequency of drinking occasions was multiplied with the amounts of ethanol for each beverage and summed up across all beverages.

Previous research has shown that when people are asked to estimate their average alcohol consumption over a past period they tend to report median, not mean quantities, and thus underestimate their actual consumption (Gruenewald & Nephew, 1994). A couple of studies compared self-reports of alcohol-consumption obtained by QF and prospective weekly diary methods and came to the conclusion that a weekly drinking diary yielded more alcohol consumption than QF measures, especially for heavy drinkers (Heeb & Gmel, 2005; Werch, 1989; but see O'Hare, 1991)). Although weekly drinking diaries are less prone to recall errors, they are very resource demanding and are not very useful for identification of typical drinking patterns (Rehm, Greenfield, Walsh, Xie, Robson, & Single, 1999). Hence, one random week is not necessarily representative for one’s drinking behavior in general. The goal of the present study was to investigate whether health cognition can predict alcohol consumption. Thus, the rank order of the participants and not the absolute amounts of consumed alcohol was of interest. Therefore a QF-measure of alcohol consumption was chosen.

3.2.1.4 Smoking

Smoking behavior was assessed by asking participants to classify themselves as someone who had never smoked, someone who only smokes occasionally, someone who is a former smoker, and someone who is smoking on a regular basis (cf. Renner et al., 1996). The smokers had to identify how many cigarettes they smoke during a day. This single item measure has been shown to relate to disease risk (cf. M. R. Law, Morris, Watt, & Wald, 1997; Nuorti et al., 2000) and was found to be a valuable indication of heaviness of smoking when compared with biological markers (Heatherton et al., 1989).

3.2.2 Health Cognitions

In this section the description of the general and behavior-related health cognition measures will be given.

3.2.2.1 Risk Perception

Risk perception items were adopted from Perloff and Fetzer (1986) and measure perceived vulnerability for coronary health problems. Participants were asked to estimate the likelihood of getting one of the following health problems during their lifetime: hypertension, hypercholesteremia, cardiovascular disease and heart attack. The responses were made on 7-point Likert scales ranging from 1 (very unlikely) to 7 (very likely). Internal consistency of the scale was good (Cronbachs's $\alpha = .89$ at T1 and $\alpha = .93$ at T2).

3.2.2.2 Outcome Expectancies

Outcome expectancies are subjective beliefs about contingencies of individual action and its consequences. Outcome expectancies were assessed by using different domain specific scales developed by Renner et al. (1996). The items comprised if/then statements. The if-condition specifies the target behavior (nutrition habits, physical activity, alcohol or cigarette consumption), whereas the then-condition consists of a possible positive consequence of the behavior. All items were constructed in a personalized manner e.g. the target behavior had to be performed by the persons themselves (If I start exercising regularly, I will be less vulnerable for cardiovascular diseases). The answers were given on a four-point Likert scale ranging from 1 (not at all true) to 4 (exactly true). Nutrition-related outcome expectancies were measured with six items (Cronbachs's α = .83 at T1 and α = .79 at T2). The 10-item physical activity-related outcome expectancies scale had good internal consistency characteristic, with Cronbachs's α = .91 at T1 and α = .92 at T2. Alcohol-related outcome expectancies were measured with four items (Cronbachs's α = .91 at T1 and α = .93 at T2). The seven item smoking-related outcome expectancies scale had good internal consistency characteristics, with Cronbachs's α = .91 at T1 and α = .92 at T2.

3.2.2.3 Behavioral Intentions

Behavior intentions are explicit decisions to act in a certain way. They reflect both the direction and the intensity of personalized goals (Sheeran, 2002). Domain specific behavioral intentions were assessed by the items developed by Renner et al. (1996). Participants completed a three item scale as a nutrition-specific intention measure. They were asked whether they intend to e.g., reduce the consumption of fatty food in the next couple of months (Cronbachs's α = .78 at T1 and α = .84 at T2). The intentions to be physically active, to quite smoking and to limit alcohol consumption were assessed with a single item respectively. Responses on all intentions scales were made on 7-point Likert scale, ranging from 1 (don't intend at all) to 7 (strongly intend).

3.2.2.4 Perceived Self-Efficacy

Perceived self-efficacy stands for "people's beliefs about their capabilities to exercise control over events that effect their lives" (Bandura, 1997). The items are formulated in such a way that a person has to indicate whether he/she feels capable of performing a target behavior, in spite of anticipated barriers. These self-efficacy beliefs are phase-specific beliefs as proposed by Luszczynska and Schwarzer (2003) and their strength may vary within a self-regulatory cycle. The self-efficacy beliefs were therefore assessed in a phase-specific manner. Responses on all self-efficacy scales were made on 4-point Likert scales, ranging from 1 (not at all true) to 4 (exactly true).

With regard to nutrition participants were asked to indicate, whether they felt confident to adopt a preventive nutrition behavior in spite of different barriers (Renner et al., 1996). Two subscales assessing action and coping nutrition-related self-efficacy were build in accordance with Schwarzer and Renner (2000). The nutrition-related action self-efficacy is important for the initiation of nutrition behavior change. The measure of action self-efficacy consisted of two items (r = .66 at T1 and r = .65 at T2). Nutrition-related coping self-efficacy is crucial for the maintenance of newly acquired favorable nutrition habits. The measure of coping self-efficacy consisted of three items (Cronbachs's α = .86 at T1 and α = .86 at T2).

Phase-specific physical activity related self-efficacy was assessed in accordance with Sniehotta et al. (2005) by two scales: action and coping self-efficacy. Action self-efficacy is important for the initiation of physical activity. Action self-efficacy contains people's beliefs in their confidence to start being physical active, when faced with different obstacles and was assessed with three items (Cronbachs's α = .87 at T1 and α = .89 at T2). Coping self efficacy is important during the volitional phase. Coping self-efficacy describes optimistic beliefs about one's ability to overcome barriers that occur during the maintenance process. It was assessed with 11 items (Cronbachs's α =.96 at T1 and α = .95 at T2).

An alcohol-related self efficacy scale developed by Renner et al. (1996) was used to capture a person's beliefs in their ability to refrain from this health impairing habit. Only alcohol-related action self efficacy was assessed. Three items were formulated by asking participants how confident they were that they can limit or abandon completely their alcohol consumption (Cronbachs's α = .83 at T1 and α = .85 at T2).

Smoking related self-efficacy is conceptualized as an optimistic belief in one's own capability to quite smoking in spite of different barriers. It was measured in two ways: as action self efficacy and coping self efficacy. Smoking-related action self-efficacy was measured by nine items (Cronbachs's α = .97 at T1 and α = .96 at T2) and assessed peoples' confidence to quit in spite of anticipated difficulties in the planning phase. The three items (Cronbachs's α = .95 at T1 and α = .94 at T2) assessing smoking-related coping self-efficacy were designed to capture people's confidence to remain a non-smoker in the volitional phase when they were directly confronted with barriers and seatbacks.

3.2.2.5 Planning

The distinction was made between *action and coping planning*. Action planning specifies in detail how and under what situational circumstances an intended action is to be implemented. Coping planning on the other hand specifies what to do in the situations that jeopardize the implementation of intended goals. The domain-specific items were developed after Sniehotta et al. (2006) and were used to capture these constructs. Responses to all action and coping planning scales were made on 4-point Likert scales, ranging from 1 (not at all true) to 4 (exactly true).

The two nutrition-related action planning items were assessed by asking participants whether they already made concrete plans of how and when they will improve their nutrition habits ($r = .85$ at T1 and $r = .78$ at T2). Nutrition-related coping planning was measured by three items. Participants were asked to rate whether they already made concrete plan about what to do in situations that might block the implementation of the intended goal to improve their nutrition behavior (Cronbachs's $\alpha = .90$ at T1 and $\alpha = .90$ at T2).

For the assessment of physical activity-related action planning, a five item scale was used. Participants had to indicate whether they already made a concrete plan of how, when, where etc. they will be physical active (Cronbachs's $\alpha = .94$ at T1 and $\alpha = .94$ at T2). Physical activity related coping planning was assessed by four items. Participants had to indicate whether they made concrete plans how to cope with e.g. missed exercise session (Cronbachs's $\alpha = .94$ at T1 and $\alpha = .94$ at T2).

Alcohol-related action planning was assessed with a three item scale. Participants were asked to estimate whether they already made concrete plans how, when and where they will limit their alcohol consumption (Cronbachs's $\alpha = .95$ at T1 and $\alpha = .94$ at T2). A three item scale was used to assess alcohol related coping planning. Respondents had to indicate whether they already made a concrete plan how to e.g., deal with relapses into the old drinking habit (Cronbachs's $\alpha = .95$ at T1 and $\alpha = .95$ at T2).

Finally, smoking-related action planning was assessed with two items by asking participants if they already had a concrete plan how and when they would quit smoking ($r = .90$ at T1 and $r = .92$ at T2). A three item scale was used to assess smoking related coping planning. Participants indicated whether they already made a concrete plan how to e.g., deal with relapses into the old smoking habit (Cronbachs's $\alpha = .95$ at T1 and $\alpha = .94$ at T2).

3.3 DESCRIPTION OF THE LONGITUDINAL SAMPLE AND DROP-OUT

Longitudinal data collected for both waves were available from 697 persons (51.3% of all Wave 1 participants). In order to investigate whether the longitudinal sub-sample was representative of the initial sample, the Wave 1 responses of the participants who completed both questionnaires (N=697) were compared with those who completed the questionnaire only at baseline (N=662). In the next section the results of the drop out analysis for the health behaviors and health cognitions are summarized.

3.3.1 Drop-out Analysis of Health Behaviors

Drop outs did not differ from those participants who remained in the study with regard to their nutrition style $t(1129) = 1.69$, n.s., the amount of consumed alcohol $t(905) = .37$ n.s., and with regard to their smoking status χ^2 (3) = 5.69, n.s. However, the drop-out participants were slightly less physically active $t(1107) = 2.03$, $p = .04$ and consumed slightly more cigarettes than the participants in the longitudinal sample $t(324) = 2.04$, $p = .04$. Means and standard deviations for the drop-out participants and the continuers are summarized in Table 4.

Table 4: Description of health behaviors of dropped-out participants and continuers

	M		SD		N	
	W1	W1 & W2	W1	W1 & W2	W1	W1 & W2
Nutrition style	2.45	2.41	.49	.47	518	613
Physical activity	4.42	5.01	4.78	4.85	511	598
Alcohol consumption	43.01	40.18	120.42	107.34	426	481
Cigarette consumption	14.97	13.39	7.55	6.44	150	176

3.3.2 Drop-out Analysis for Health Cognitions

Risk perception: There were no differences between participants in the longitudinal sub-sample and the participants who dropped out from the longitudinal study with regard to absolute risk perception $t(681.58) = 1.65$, n.s. Thus, the participants in the drop-out sub-sample ($M = 3.73$, $SD = 1.14$) did not differ systematically from the participants in the longitudinal sub-sample ($M = 3.58$, $SD = 1.29$) regarding absolute risk perception.

Outcome expectancies: Investigation of differences between the longitudinal sub-sample and the sub-sample with dropped out participants revealed that there were no mean differences with regard to nutrition-related outcome expectancies, $t(1110) = 1.73$, ns. There were no group differences with regard to exercise-related outcome expectancies $t(1108) = 1.03$, n.s. The same was true both for alcohol-related outcome-expectancies, $t(907) = 1.13$, n.s., and for smoking-related outcome expectancies, $t(278) = 1.65$, n.s. The means and standard deviations are summarized in Table 5.

Table 5: Description of domain-specific outcome expectancies of dropped-out participants and continuers

	M		SD		N	
Outcome expectancies in the domain of:	W1	W1 & W2	W1	W1 & W2	W1	W1 & W2
Nutrition	2.86	2.79	.63	.66	509	603
Physical activity	3.29	3.32	.52	.53	507	606
Alcohol consumption	3.06	3.00	.82	.88	421	488
Cigarette consumption	3.18	3.30	.59	.60	120	160

Self-efficacy: Participants in the longitudinal sub-sample did not differ from those who had filled out the questionnaire only at baseline with regard to nutrition-related action self-efficacy $t(1093) = .25$, n.s., and coping self-efficacy $t(1120) = 1.68$, n.s., to physical activity-related action self-efficacy $t(1099) = 1.64$, n.s. and coping self–efficacy $t(1120) = 1.68$, n.s, to alcohol-related action self-efficacy $t(889) = 1.25$, n.s. and to both smoking-related action self-efficacy $t(277) = .77$, n.s., and coping self-efficacy $t(277) = .25$, n.s.. The means and standard deviations are summarized in Table 6.

Table 6: Description of domain-specific self-efficacy of dropped-out participants and continuers

	M		SD		N	
	W1	W1 & W2	W1	W1 & W2	W1	W1 & W2
Nutrition-related:						
Action self-efficacy	2.63	2.64	.72	.73	504	597
Coping self-efficacy	2.55	2.62	.55	.62	505	597
Physical activity-related:						
Action self-efficacy	3.09	3.16	.75	.74	503	592
Coping self-efficacy	2.62	2.68	.64	.63	514	608
Alcohol-related:						
Action self-efficacy	3.02	2.94	.84	.92	413	478
Smoking-related:						
Action self-efficacy	2.35	2.43	.80	.85	120	159
Coping self-efficacy	2.47	2.50	.84	.89	120	159

Intentions: Participants in the longitudinal study did not differ from those who filled out only the first questionnaire with regard to intention to quite smoking $t(277) = 1.45$, n.s. Participants in the drop-out sub-sample had stronger intentions to eat healthier $t(1143) = 3.45$, $p < .001$, to be physically active $t(1117.07) = 2.25$[3], $p < .05$ and to reduce alcohol consumption $t(1131.87) = 3.79$, $p < .001$, in comparison to the longitudinal sub-sample. The means and the standard deviations are summarized in Table 7.

Table 7: Description of intentions of dropped-out participants and continuers

	M		SD		N	
Intentions to:	W1	W1 & W2	W1	W1 & W2	W1	W1 & W2
eat healthier	4.67	4.40	1.21	1.41	530	615
be physical active	4.84	4.61	1.43	1.94	530	615
limit alcohol consumption	4.12	3.73	1.48	1.90	530	615
quite smoking	3.25	2.90	1.94	2.04	120	159

Planning: The drop-out with regard to planning proved to be not systematic. Participants in the longitudinal sub-sample did not differ from those who had filled out the questionnaire only at baseline. Because of the high intercorrelations between action and coping planning constructs across all domains (all *r's* > .75), for the

[3] Due to the significant result of the Levene's test for equality of variances $F(1117) = 73.48$, $p < .001$ the degrees of freedom are not rounded.

following analyses the two scales were collapsed into a single planning scale. The results of t-tests were as follow: with regard to nutrition-related planning $t(1102) = 1.37$, n.s., to physical-activity related planning $t(1102) = 1.57$, n.s., to alcohol related planning $t(853) = .48$, n.s. and to smoking-related planning $t(277) = .27$, n.s. The means and standard deviations are summarized in Table 8.

Table 8: Description of domain-specific planning of dropped-out participants and continuers

	M		SD		N	
	W1	W1 & W2	W1	W1 & W2	W1	W1 & W2
nutrition planning	2.20	2.28	.84	.85	505	699
physical activity planning	2.40	2.45	.67	.70	514	608
alcohol planning	2.17	2.14	1.03	1.01	392	463
smoking planning	2.25	2.22	.91	.95	120	159

To summarize, the study participants that took part in both waves of the study for the most part did not differ systematically on the core variables from the participants that only took part in the first wave of the study. The difference discovered between participants who did versus did not continue pertained only to the differences in intentions, the level of physical activity and the amount of consumed cigaretts. The continuers had lower intention to adopt healthier nutrition, to be physically active and to reduce alcohol consumption. However, these differences were relatively small (all of them were much smaller than half of the standard deviations of the respective variables). Accordingly, biases induced by drop-out from the study should be limited.

3.4 ANALYSES

The following sections give a general overview of the statistical methods employed to test the central hypotheses of the present study. In the first part, the treatment of missing values and outliers will be described. Following this, an overview of central methods of data analysis will be given. Statistical analyses were conducted using SPSS for Windows 12.0, AMOS for Windows 5.0 and LatentGOLD® 4.0.

3.4.1 Treatment of Missing Values and Outliers

Any large survey study is inevitably confronted with the missing data problem. A number of methods on how to treat missing values were proposed in the literature (cf. R. J. A. Little & Rubin, 1987; Schafer & Graham, 2002). The appropriateness of a certain method depends on the underlying assumptions regarding the distribution type of missingness. Schafer and Graham (2002) distinguish between three kinds of missingness: a) missing completely at random (MCAR); b) missing at random (MAR) and c) missing not at random (MNAR). Only if the missing values follow MCAR or MAR distribution is the unbiased estimation of missing values possible. The distribution of missingness is usually unknown to researchers. However it is assumed that in many psychological research settings, the departures from MAR might be negligible (Schafer & Graham, 2002). Therefore, it was assumed that the missing data in the present study follow at least MAR distribution. This means that a missing value on a certain variable might depend on the values of other variables in the dataset but not on the data that was actually missing.

It was decided to use a twofold approach for the estimation of the missing values. On the *variable level,* missing values were estimated using a regression method that under the MAR assumption outperforms common data handling strategies (listwise/pairwise deletion, mean substitution) (cf. R. J. A. Little & Rubin, 1987; Schafer & Graham, 2002) that would demand a MCAR-distribution, i.e. a distribution where missing values are independent of any of the data values. Regression estimation was performed using the SPSS Missing Value Analysis Module. Missing values were estimated if a missing response was a part of a scale with more than two items, and if a response was given for at least 50% of the remaining items of that scale. Age, sex and the responses to the remaining items of a scale with missing values were then predictors for the missing items (Tabachnick & Fidell, 2001). Missing values were not estimated if they pertained to single item indicators. On the *parameter estimation level,* within a structural equation modeling framework, missing values were estimated using a Maximum Likelihood (ML) estimation algorithm implemented in the AMOS-software. In numerous simulation studies it was shown that under assumption of MAR, ML-method produces an unbiased parameter estimation (Allison, 2003; Gold & Bentler, 2000; Schafer & Graham, 2002).

Prior to the analyses the data was screened for the univariate and multivariate outliers. An observation was considered to be an univariate outlier if it's z-score exceeded $|3.29|$ (Tabachnick & Fidell, 2001). In this case, the value of an outlier was adjusted to the closest non-outlying value in the data distribution. Preceding analysis, data was routinely screened for multivariate outliers and those were identified on the basis of Mahalonobis distance ($p < .001$) using SPSS Regression (Tabachnick & Fidell, 2001). The few cases that were detected as multiple outliers were removed from the subsequent analysis (see Results chapter).

3.4.2 General Analytic Procedures

As a starting point for all data analyses, bivariate associations were screened using Pearson correlations, t-tests and chi-square tests. Multivariate relationships between constructs under study were explored by the means of analyses of variance, structural equation modeling and latent cluster analysis.

3.4.2.1 Analyses of Variance (ANOVA)

ANOVAs were performed to investigate age-related differences in health behaviors and health cognitions. Since the two investigated age groups had an unequal sample sizes, homogeneity of variances was tested with Levine's test for homogeneity of variances. Violation of homogeneity of variance was assumed when Levine's test was significant at $p < .01$. In this case a more stringent Alpha level was chosen (e.g. for moderate violation with nominal $\alpha = .05$, an $\alpha = .025$ was chosen; for severe violations an $\alpha = .01$ was chosen).

Whenever multiple tests with the same independent variable were performed (e.g. comparisons between the three clusters) the adjustments of the alpha-level were performed in order to reduce type I error inflation. Bonferoni adjustment strategy was used, e.g. the alpha level (.05) was divided by the number of the performed tests.

3.4.2.2 Structural Equation Modeling (SEM)

The applicability of the HAPA-model in different settings was tested using structural equation modeling. For all constructs except risk perception, action self-efficacy, and intentions, parcels were used to create indicators for latent variables within a structural equation approach (for more details see Tabels B 1-4 in Appendix B). Considering the complexity of the HAPA model, the more parsimonious models with parcel data appear more advisable since this approach reduces the number of estimated parameters both locally in defining a construct and globally in representing an entire model. Additionally, residuals are less likely to be correlated (both because fewer indicators are used and because unique variances are smaller), and it leads to reductions in various sources of sampling errors (MacCallum, Widaman, Zhang, & Hong, 1999). For parceling, a random assignment method suggested by T. D. Little, Cunningham, Shahar, and Widaman (2002) was chosen, since all single item loadings were equally high, and all latent constructs were one-dimensional.

The model fit was assessed by examining the comparative fit index (CFI), the Tucker-Lewis-Index (TLI), and the root-mean-square error of approximation (RMSEA). A model is judged to have a good fit if CFI and TLI indices have values higher than .90, the value of RMSEA is smaller than .08, the lower bound of 90% confidence intervals (CI) is close to zero, and the upper bound of the 90% CI does not exceed .10 (Tabachnick & Fidell, 2001). Since the χ^2 statistic is sample size dependent, the χ^2/df ratio was employed as a further goodness of fit criterion. Bollen and Long (1993) suggest a χ^2 not larger than 2-5 times the degrees of freedom.

3.4.2.3 Latent Cluster Analysis (LCA)

In order to establish patterns of health behaviors, a cluster analysis was performed using a Latent Class Analysis (LCA) approach. LCA is a statistical method for defining subtypes of related cases (i.e. latent classes) from multivariate categorical data, according to similarities in their response patterns (for the detailed review see Bartholomew, 1987; Lazarsfeld & Henry, 1968). LCA is one kind of cluster analysis which utilizes a model-based method i.e. involves the specification of statistical distributions (Magidson & Vermunt, 2002). In contrast to more well-known clustering methods such as K-means clustering which apply arbitrary distance metrics to group individuals based on their similarity, LCA-method derives clusters based on conditional independence assumptions (Clogg, 1995). Using statistical distributions rather than distance metrics to define clusters allows researchers to determine whether a model with a particular number of clusters is able to fit the data, since tests can be performed for observed versus model expected values.

Models estimating different numbers of health behavior patterns were fitted to the data using Latent Gold 4.0, a maximum-likelihood estimation LCA software program (Vermunt & Magidson, 2005). The fit of each model was evaluated using the likelihood ratio chi square (L^2 value with associated p value), Bayesian information criterion (BIC), Akaike information criterion (AIC), Akaike information criterion 3 (AIC3), bivariate residuals, entropy measures and magnitude of classification errors. A more detailed description of the goodness of fit indices will be given in the results chapter (see section 4.1.3).