



# Structural Validation and Measurement Invariance of the HLS-Q12 Health Literacy Instrument in Finnish Adults: Comparing Traditional and Alignment Methods

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**Objectives:** To examine the internal structure, internal consistency, and measurement invariance of the HLS-Q12 across sociodemographic groups in Finnish adults, using traditional multi-group confirmatory factor analysis (MGCFAs) and alignment optimization.

**Methods:** We analyzed data from 7,077 Finnish adults drawn from a nationally representative national sample (n = 4,003) and a regional sample from North Savo (n = 3,074). Analyses included confirmatory factor analysis, MGCFAs, and alignment optimization with Monte Carlo evaluation. Invariance was examined across gender, age, education, and study samples.

**Results:** Reliability was high ( $\alpha = 0.905$  &  $\omega = 0.896$ ) and unidimensional structure (CFI = 0.951, TLI = 0.935, RMSEA = 0.058). MGCFAs supported scalar invariance for gender, education, and study samples. Alignment optimization exhibited acceptable non-invariance (2.8%–25% of parameters), primarily in intercepts. Women and individuals with higher education showed higher health literacy; young adults exhibited higher levels than older cohorts.

**Conclusion:** The Finnish HLS-Q12 supported subgroup comparisons for population monitoring, with largely adequate measurement invariance across key sociodemographic groups. The evidence pertains primarily to internal structure and measurement invariance. Further studies should examine additional validity evidence using external criteria.

**Keywords:** alignment method, health literacy, HLS-Q12, measurement invariance, structural validation

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## INTRODUCTION

Health literacy has increasingly been recognized as a critical determinant of health outcomes and health equity across diverse populations and systems. Defined as the knowledge, motivation, and competencies needed to access, understand, appraise, and apply health information for health-related decision-making throughout the life course [1], health literacy enables individuals to navigate complex health-related environments across society, including those with healthcare systems

effectively. Recent research highlights that health literacy is not a static or purely individual trait, but a dynamic and context-dependent capability shaped by social, cultural, and organizational factors [2]. The World Health Organization [3] emphasizes that health literacy is mediated by the structures and resources of society, and that improving it requires inclusive access to education, equitable communication, and supportive environments.

Limited health literacy has been associated with a wide range of adverse health-related consequences such as poorer health outcomes and poorer use of healthcare services [4], medication errors [5], increased mortality [6], and even a higher likelihood of emergency department revisits after discharge [7].

Moreover, low health literacy disproportionately affects marginalized groups, reinforcing health disparities related to socioeconomic status, education, ethnicity, and language [5, 8]. These disparities extend across generations, as parents' health literacy influences their children's health-related knowledge and behaviors, creating lasting effects on family and population health [9].

The COVID-19 pandemic further highlighted the critical importance of health literacy for understanding health information and making informed health decisions [10–12]. It underscored the need for accessible, trustworthy, and culturally sensitive communication, especially in times of uncertainty and rapid change. The European Health Literacy Survey (HLS-EU) found that approximately 47% of Europeans have limited health literacy, with substantial variations between countries and population groups [13]. While the comprehensive HLS-EU-Q47 instrument advanced health literacy measurement significantly, its length posed practical challenges in surveys and clinical settings [14, 15]. To address this limitation, Finbråten et al [16] developed the HLS-Q12, a parsimonious 12-item version validated in Norwegian adults. Recent validation studies using the HLS-Q12 in Brazil [17] and rural Bangladesh [18] have confirmed cross-cultural applicability of this instrument, supporting its use in diverse contexts.

Among available health literacy instruments, we selected the HLS-Q12 for this study based on several considerations. First, the HLS-Q12 is brief and feasible for inclusion in population surveys, reducing respondent burden while retaining coverage of key health literacy domains [16]. Second, it is grounded in the European Health Literacy Survey conceptual framework, which supports cross-national comparisons [19]). Third, its focus on perceived difficulty in accessing, understanding, appraising, and applying health information aligns with our methodological aim to evaluate measurement equivalence across sociodemographic groups, which is essential for population monitoring and subgroup comparisons [20].

Despite Finland's advanced healthcare system, universal health coverage, and high education levels, health literacy challenges persist, particularly among vulnerable groups and with evolving digital health communication demands [21, 22]. For example, older adults with multiple chronic conditions may

face challenges in maintaining active engagement in health-related activities without sufficient health literacy [23]. Finnish studies have developed context-specific instruments and have applied internationally validated tools such as the HLS-EU-Q16 in selected adult samples [23], and created an instrument for school-aged children [24]. However, large-scale adult validation and the systematic use of full international instruments remain limited, constraining cross-national comparability and policy development. This represents a significant gap in Finland's capacity to monitor population health literacy and to contribute systematically to international health literacy research.

When comparing health literacy across different demographic groups, measurement invariance becomes crucial to ensure that instruments function equivalently across populations [20, 25]. Traditional multi-group confirmatory factor analysis (MGCFA) requires strict conditions often unmet in real-world data [26]. The alignment optimization method offers a more flexible approach, accommodating partial measurement invariance while enabling meaningful group comparisons [27, 28]. This method has shown superior performance compared to traditional approaches in recent studies [29, 30].

Accordingly, we examined the internal structure, internal consistency, and measurement invariance of the HLS-Q12 in Finnish adults using MGCFA and alignment optimization. Specifically, we aimed to: (1) examine the unidimensional factor structure and internal consistency of the HLS-Q12; (2) test measurement invariance across gender, age, education, and study samples; and (3) compare findings from traditional MGCFA and alignment optimization approaches as complementary approaches for evaluating cross-group comparability.

## METHODS

### Participants and Data Collection

Data were drawn from a broader health and wellbeing survey (PROM) conducted in Finland in 2024. Data collection was implemented in collaboration with two Finnish research agencies, Innolink and Bilend. A nationally representative sample ( $n = 4,003$ ) was recruited via Bilend's population panel using quota-based procedure to approximate the adult population distribution in regard to gender, age and geographical region. In addition, a complementing self-selected sample from the North Savo region was collected ( $n = 3,083$ ) through multiple routes, including additional non-quota panel recruitment via Innolink and Bilend and dissemination of survey links by the Wellbeing Services County of North Savo (PSHVA) through its communication networks and outreach channels. The combined of the national and regional samples yielded  $N = 7,086$  participants, with 7,077 cases retained after excluding participants with incomplete HLS-Q12 responses.

Participants were adults aged 18 years and older residing in Finland. All procedures were conducted in accordance with the

**TABLE 1** | Demographic characteristics of the analytic sample (Health and wellbeing survey, Finland, 2024).

Category	Groups	Total sample	National sample	North Savo
Age (N = 7,077)	18–34	22.9	25.3	19.9
	35–49	27.3	28.4	25.8
	50–64	26.9	25.8	28.4
	65–89	22.9	20.5	25.9
Gender (N = 7,028)	Male	36.4	48.1	21.3
	Female	63.6	51.9	78.7
Education level (N = 7,073)	Basic education (comprehensive school)	7.2	8.2	5.9
	Vocational upper secondary education	30.4	31.6	28.9
	General upper secondary education	9.5	10.4	8.4
	Post-secondary non-tertiary education	11.7	11.0	12.5
	University of applied sciences	20.7	19.2	22.6
	University	20.5	19.6	21.7
Study sample (N = 7,077)	National sample	56.5	—	—
	Regional sample	43.5	—	—

**TABLE 2** | Standardized factor loadings for the HLS-Q12 items from the confirmatory factor analysis Model (Health and wellbeing survey, Finland, 2024).

Item	Standardized factor loadings	Standard error	P-value
Q1	0.673	0.009	0.000
Q2	0.682	0.008	0.000
Q3	0.701	0.008	0.000
Q4	0.592	0.009	0.000
Q5	0.685	0.008	0.000
Q6	0.618	0.010	0.000
Q7	0.678	0.008	0.000
Q8	0.674	0.009	0.000
Q9	0.712	0.007	0.000
Q10	0.656	0.008	0.000
Q11	0.753	0.007	0.000
Q12	0.621	0.009	0.000

Standardized factor loadings (*λ*) are reported from the final CFA, model. All loadings were statistically significant at  $p < .001$ . Four residual covariances were added between Q6–Q4, Q7–Q8, Q9–Q11, and Q10–Q11 to improve model fit.  $N = 7,077$ .

Declaration of Helsinki and data protection regulations. The study involved anonymous online survey data collection with informed consent from all participants. Under Finnish national guidelines for ethical review in human sciences [31], formal ethics committee pre-evaluation is not required for the present study. The survey was administered online using established survey protocols with informed consent procedures.

## Measures

Health literacy was assessed using the HLS-Q12 [16] as described by Zanini et al [17]. This instrument evaluates individuals' perceived difficulty in accessing, understanding, appraising, and applying health information across healthcare, disease prevention, and health promotion domains. Each item begins with "In your daily life, how easy or difficult is it for you to... ", followed by specific health-related tasks (e.g., "...understand information about recommended health screenings or examinations"). The instrument was translated from English into Finnish by members of the researcher team with professional proficiency in both Finnish and English and subsequently reviewed within the team to ensure clarity and

conceptual consistency with the original items. Responses were rated on a 4-point Likert scale (1 = *very difficult* to 4 = *very easy*), with higher scores indicating greater health literacy.

## Statistical Analyses

Descriptive statistics were computed using SPSS 29.0 [32]. All validation analyses were conducted using Mplus 8.11 [33] with robust maximum likelihood estimator, which provides standard errors and test statistics robust to non-normality when treating the 4-point items as approximately continuous [34]. Missing data analysis revealed a Missing at Random (MAR) pattern, addressed using Full Information Maximum Likelihood (FIML) estimation. Item-level missingness was low (0.4%–1.6%).

Psychometric validation followed a sequential approach: (1) confirmatory factor analysis (CFA) to test the unidimensional structure, (2) MGCFA to examine measurement invariance across gender, age cohorts (18–34, 35–49, 50–64, 65–74, 75–89), education levels (basic education, Vocational upper secondary education, General upper secondary education, Post-secondary non-tertiary education, college, university of applied sciences, university), and study samples (sampling source from national vs. regional), and (3) alignment optimization method as an alternative approach to handle partial measurement invariance.

Model fit was assessed using the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Acceptable fit thresholds were CFI/TLI  $\geq 0.90$  (good fit  $\geq 0.95$ ), RMSEA  $\leq 0.08$  (good fit  $\leq 0.06$ ), and SRMR  $\leq 0.08$  (preferably  $\leq 0.06$ ) [35]. The chi-square-to-degrees-of-freedom ratio ( $\chi^2/df$ ) was reported in **Supplementary Material** for completeness but not used as a primary fit indicator due to its well-documented sensitivity to large sample sizes [35, 36].

Measurement invariance was assessed using Chen's [26] criteria:  $\Delta CFI \leq 0.01$ ,  $\Delta RMSEA \leq 0.015$ ,  $\Delta SRMR \leq 0.030$  for metric and  $\leq 0.010$  for scalar invariance.

The alignment optimization method accommodates partial non-invariance by identifying non-invariant parameters while enabling meaningful group comparisons. Fixed alignment

**TABLE 3** | Measurement invariance of HLS-Q12 across the different groups (gender, education, age, study sample) (Health and wellbeing survey, Finland, 2024).

Group/model	$\chi^2$ (df)	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$ ( $\Delta$ df)	$\Delta$ CFI	$\Delta$ RMSEA	$\Delta$ SRMR
Gender									
Configural model	1,318.159 (100)	0.949	0.933	0.059	0.033				
Metric model	1,366.007 (111)	0.947	0.937	0.057	0.035	47.848 (11)	-0.002	-0.002	0.002
Scalar model	1,613.026 (122)	0.938	0.932	0.059	0.039	247.019 (11)	-0.009	0.002	0.004
Education level									
Configural model	1,507.401 (300)	0.950	0.934	0.058	0.035				
Metric model	1,636.811 (355)	0.947	0.941	0.055	0.045	129.410 (55)	-0.003	-0.003	0.010
Scalar model	1869.337 (410)	0.940	0.942	0.055	0.050	232.526 (55)	-0.007	0.000	0.005
Age cohort									
Configural model	1,402.348 (200)	0.952	0.937	0.061	0.033				
Metric model	1,526.251 (233)	0.949	0.942	0.056	0.046	123.903 (33)	-0.003	-0.005	0.013
Scalar model	2018.906 (266)	0.931	0.931	0.061	0.058	492.655 (33)	-0.018	0.005	0.012
Study sample									
Configural model	1,332.421 (100)	0.950	0.934	0.059	0.033				
Metric model	1,384.450 (111)	0.948	0.938	0.057	0.036	52.029 (11)	-0.002	-0.002	0.003
Scalar model	1,502.991 (122)	0.944	0.939	0.057	0.040	118.541 (11)	-0.004	0.000	0.004

$\chi^2$ , chi-square test statistic; df, degrees of freedom; p, probability value; CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual;  $\Delta\chi^2$ , likelihood ratio test (difference in chi-square between nested models);  $\Delta$ CFI, change in CFI;  $\Delta$ RMSEA, change in RMSEA;  $\Delta$ SRMR, change in SRMR. Measurement invariance was evaluated following Chen's (2007) guidelines:  $\Delta$ CFI  $\leq$  0.010,  $\Delta$ RMSEA  $\leq$  0.015, and  $\Delta$ SRMR  $\leq$  0.030 for metric and  $\leq$  0.010 for scalar invariance. All p-value  $<$  0.001.

(ALIGNMENT = FIXED) was implemented based on model identification requirements. Solution quality was evaluated by the proportion of non-invariant parameters, with values up to 25% regarded as favorable [27, 30]. Monte Carlo (MC) simulations (1,000 replications) validated parameter recovery, with correlation coefficient of 0.98 or greater indicating trustworthy results [27, 37].

Latent mean comparisons were conducted using a stratified approach to examine result consistency and assess potential selection bias. First, demographic group comparisons were performed using the combined sample for maximum statistical power. Subsequently, separate analyses were conducted within the national sample (n = 3,998) and regional sample (n = 3,079) to evaluate the stability of demographic patterns across sampling frames. Comparisons were limited to groups achieving adequate measurement invariance in both MGCFA (scalar level) and alignment approaches ( $\leq$ 25% non-invariance with acceptable Monte Carlo validation).

## RESULTS

### Descriptive Statistics

Descriptive statistics were computed for the total sample (N = 7,077) and the results are exhibited in **Table 1**. The mean age was 49.52 years (SD = 16.27; range = 18–89), and 22.8% were aged 65 years or older. Women represented 63.6% of the sample (n = 4,472), with 36.4% men (n = 2,556). Educational attainment was diverse, 7.2% comprehensive, 30.4% vocational/technical, 9.5% high school, 11.7% college, 20.7% university of applied sciences, and 20.5% university. The national sample constituted 56.5% and the regional North Savo sample 43.5%.

Item-level descriptives are presented in **Supplementary Table S1**. Item means ranged from 2.86 to 3.53 (scale 1–4), with standard deviations (SD) between 0.59 and 0.78. Missingness

was minimal (0.4%–1.6% per item), suggesting limited item nonresponse. The distribution of the total HLS-Q12 score was approximately normal with slight negative skew.

### Confirmatory Factor Analysis

An exploratory factor analysis using principal axis factoring supported a unidimensional structure for the HLS-Q12 (KMO = 0.942; Bartlett's  $\chi^2(66) = 35,155.17$ ,  $p <$  0.001). A single factor with an eigenvalue greater than 1 explained 44.7% of the variance.

CFA was conducted to test the unidimensional structure. Initial model fit was acceptable (CFI = 0.923, TLI = 0.906, RMSEA = 0.068, SRMR = 0.038). Following modification indices and theoretical considerations [38], four residual covariances were added between conceptually related items, resulting in improved fit (CFI = 0.951, TLI = 0.935, RMSEA = 0.058, SRMR = 0.032).

All items loaded significantly on the latent factor, with standardized loadings ranging from 0.592 to 0.753. Detailed loadings are reported in **Table 2**. Internal consistency reliability was excellent (Cronbach's  $\alpha = 0.905$ , McDonald's  $\omega = 0.896$ ), indicating strong scale reliability for measuring health literacy as a unified construct.

### Invariance Testing via Multi-Group Confirmatory Factor Analysis

MGCFA results demonstrated stable measurement properties across demographic groups. Full scalar invariance was achieved for gender, education, and sampling source with minimal fit deterioration ( $\Delta$ CFI  $\leq$  0.009,  $\Delta$ RMSEA  $\leq$  0.003, see **Table 3**). For age cohorts, the change in CFI at the scalar level was larger ( $\Delta$ CFI = -0.018), whereas changes in RMSEA and SRMR were small. Taken together, these results suggest some degree of age-related non-invariance, which was further examined using the alignment approach.

**TABLE 4 |** Approximate measurement invariance for item intercepts and factor loadings across groups using alignment optimization (Health and wellbeing survey, Finland, 2024).

Item number	Gender		Education level				Age cohort			Study sample				
Loading invariance														
Q1	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q2	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q3	1	2	1	(2)	3	4	5	6	1	2	3	4	1	2
Q4	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q5	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q6	1	2	1	2	3	4	5	6	1	2	(3)	(4)	1	2
Q7	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q8	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q9	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q10	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q11	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Q12	1	2	1	2	3	4	5	6	1	2	3	4	1	2
Loadings noninvariance %	0.0%		1.4%				4.2%			0.0%				
Intercepts invariance														
Q1	1	2	1	2	3	4	5	6	1	2	3	(4)	(1)	(2)
Q2	1	2	1	2	3	4	5	(6)	1	2	3	(4)	1	1
Q3	(1)	(2)	1	2	3	4	5	6	1	2	(3)	(4)	(1)	(2)
Q4	1	2	1	2	3	4	5	6	(1)	2	3	(4)	1	1
Q5	1	2	1	2	3	4	5	6	1	2	3	4	1	1
Q6	(1)	(2)	1	2	3	4	5	6	(1)	(2)	(3)	(4)	(1)	(2)
Q7	1	2	1	2	3	4	5	6	(1)	2	3	(4)	1	1
Q8	(1)	(2)	(1)	(2)	3	4	5	6	1	2	3	4	1	1
Q9	(1)	(2)	1	2	3	4	5	6	1	2	(3)	(4)	1	1
Q10	(1)	(2)	1	2	3	4	5	6	1	2	(3)	4	1	1
Q11	1	2	1	2	3	4	5	6	1	2	3	4	1	1
Q12	(1)	(2)	1	2	3	4	5	6	1	2	3	(4)	(1)	(2)
Intercepts noninvariance %	50.0%		4.2%				33.3%			33.3%				
Total noninvariance %	25.0%		2.8%				18.8%			16.7%				

Numbers represent group classifications: Gender (1 = male, 2 = female); Education (1 = Comprehensive school, 2 = Vocational/technical school, 3 = high school, 4 = college, 5 = University of applied sciences, 6 = University); Age cohort (1 = 18–34, 2 = 35–49, 3 = 50–64, 4 = 65–89); Study sample (1 = National sample, 2 = PSHVA, sample). Numbers in parentheses indicate non-invariant parameters for that item-group combination. Loading non-invariance percentage represents the proportion of factor loading parameters that differ significantly across groups within each demographic variable. Intercepts non-invariance percentage represents the proportion of intercept parameters that differ significantly across groups. Total non-invariance percentage indicates the overall proportion of measurement parameters (both loadings and intercepts) showing group differences. Alignment optimization employed fixed estimation with reference group constraints. Acceptable threshold for group comparisons: ≤25% non-invariant parameters.

## Invariance Testing via Alignment Optimization Approach

The alignment analysis provided complementary insights into measurement invariance patterns (see **Table 4** for full sample and **Supplementary Material 2, 3** for separate sample). Education comparisons showed the highest invariance quality (2.8% non-invariant parameters), followed by national/regional sample comparisons (16.7%), age cohorts (18.8%), and gender (25.0%). Non-invariance was primarily concentrated in item intercepts rather than factor loadings, indicating consistent factor structure across groups while allowing for baseline response differences.

## Latent Mean Comparisons

The results of MC simulations with 1,000 replications for two different sample sizes (see details in **Supplementary Table S4**) confirmed reliable parameter recovery across all demographic comparisons ( $r = 0.87\text{--}1.00$ ) [27]. Stratified analyses showed consistent patterns across national and regional samples, supporting result robustness. Group comparisons are therefore

reported in **Table 5** using the combined sample for optimal statistical precision (details in **Supplementary Table S5**).

Significant demographic differences emerged across all examined variables. Women scored higher than men (0.388), with clear educational gradients favoring higher education levels. Younger adults (18–34) exhibited higher estimated latent means than older adults (65+: -0.124), while middle-aged groups showed intermediate levels. The regional sample scored higher than the national sample (0.233).

## DISCUSSION

This study applied complementary analytic approaches to examine the internal structure and cross-group comparability of the HLS-Q12 among Finnish adults. By combining traditional MGCFA with alignment optimization, we provide evidence for largely adequate measurement invariance across key sociodemographic groups and summarize subgroup patterns relevant for population monitoring in Finland.

**TABLE 5** | Comparisons of latent factor means of HLS-Q12 across sociodemographic groups (Health and wellbeing survey, Finland, 2024).

Category	Groups	Factor mean
Gender	Male (reference)	—
	Female	0.388*
Age cohort	18–34 (reference)	—
	35–49	–0.057
	50–64	–0.015
	65–89	–0.124*
	Basic education (reference)	—
Education	Vocational upper secondary education	0.188*
	General upper secondary education	0.198*
	Post-secondary non-tertiary education	0.316*
	University of applied sciences	0.516*
	University	0.556*
Study sample	Regional sample (reference)	—
	National sample	–0.233*

Latent factor means were estimated using Mplus Alignment Optimization with ALIGNMENT = FIXED (reference group's mean = 0, variance = 1). Asterisks (\*) indicate significant pairwise Wald z contrasts vs. the reference group, (two-sided  $\alpha = .05$ ; SEs of robust maximum likelihood estimation). Latent means are not observed means.

Demographic patterns were consistent with slight variation across national and regional subsamples. Details in **Supplementary Table S5**.

The HLS-Q12 exhibited robust psychometric properties in the Finnish context, with excellent internal consistency and a clear unidimensional factor structure. These findings are broadly consistent with previous studies in other settings [16–18], supporting the feasibility of the HLS-Q12 across diverse populations. CFA results supported the theoretical framework underlying health literacy as a unified construct encompassing competencies across healthcare, disease prevention, and health promotion domains [1].

Our sequential analytical approach demonstrated the complementary value of traditional and innovative methods for testing measurement invariance. The alignment optimization method provided more nuanced insights than conventional MGCFA by identifying specific non-invariant parameters while accommodating partial invariance conditions. The Monte Carlo validation feature offered empirical assessment of parameter reliability unavailable in traditional approaches, with most demographic comparisons achieving excellent recovery. This methodological framework provides a replicable template for cross-cultural validation studies.

The demographic patterns observed provide important insights for Finnish health and social policy as well as international health literacy research. Higher health literacy scores among women are consistent with prior European evidence [11, 13, 39], likely reflecting greater healthcare engagement and health information-seeking behaviors. The educational gradient demonstrated clear benefits of education at all levels, with university graduates showing the highest health literacy and those with only basic education showing the largest deficits. This pattern reflects the well-documented association between educational attainment and health literacy capabilities [4, 40], highlighting the importance of educational equity for population health literacy in Finland.

The age-related patterns revealed young adults demonstrating the highest health literacy levels, showing higher estimated latent means than older adults, consistent with previous studies [41] and recent observations in Germany [42]. However, comparisons among younger and middle-aged groups showed limited significant differences, suggesting that major health literacy decline primarily occurs after age 65 rather than following a linear age gradient [43]. The relative advantage of younger adults, though not always statistically significant compared to middle-aged groups, may reflect their greater familiarity with digital health information environments that increasingly characterize modern healthcare systems [44]. This interpretation gains particular relevance in the Nordic context, where digital health services are rapidly expanding and require advanced information processing skills beyond traditional health literacy competencies, and require further studies to explore the mechanisms underlying generational differences in health literacy acquisition and expression [45].

Moreover, the finding that the regional sample demonstrated slightly higher health literacy than the national sample was also unexpected, given that rural and regional populations typically show lower health literacy in international studies [13, 46, 47]. However, place of residence, whether rural or regional, is not necessarily an independent determinant of health literacy [46]. Regional variations in this study may reflect either genuine contextual factors or methodological influences such as sampling differences, warranting cautious interpretation and further investigation with standardized recruitment approaches.

This study has several notable strengths. First, the large sample size with broad sociodemographic coverage provides robust statistical power for subgroup analyses. Second, the inclusion of both a national sample and a regional North Savo sample enables examination of sampling source effects and strengthens the robustness of subgroup comparisons. Third, the combined use of traditional and innovative method offers complementary evidence for cross-group comparability under realistic conditions [48–51]. Fourth, Monte Carlo simulations provided additional support for the stability of the main estimation results.

However, certain methodological considerations should be acknowledged. First, this study provides evidence primarily for internal structure, internal consistency, and measurement invariance across key sociodemographic groups. We did not examine other sources of validity evidence, including convergent and discriminant validity with alternative health literacy instruments, criterion validity against external benchmarks, or predictive validity for subsequent outcomes. Although subgroup differences are reported after establishing measurement invariance, these comparisons are intended for population monitoring and should not be interpreted as formal known-groups validity evidence in the absence of external criteria. Future research should strengthen the validity evidence base by linking the HLS-Q12 to theoretically relevant external criteria and longitudinal outcomes.

Second, the Finnish version was developed and reviewed within the research team and did not include a formal forward-backward translation protocol with systematic cognitive debriefing, which

may affect cross-cultural comparability. Future work can strengthen semantic and conceptual equivalence by applying standardized translation and cultural adaptation procedures, including cognitive interviewing.

Third, the cross-sectional design limits temporal inference. The sampling approach, which combined a nationally representative online panel with a regional sample using multiple recruitment channels, may affect generalizability. Potential selection bias should be considered when interpreting subgroup differences, particularly for national versus regional comparisons. In addition, health literacy was measured using self-reported perceived difficulty items, which may be influenced by response styles.

These findings support the feasibility of monitoring population health literacy using an internationally recognized instrument. Our findings demonstrate that health literacy varies significantly across demographic groups in predictable patterns, with education and age emerging as key correlates requiring targeted public health attention. The successful application of both traditional and innovative measurement invariance methods confirms that meaningful group comparisons are possible despite minor measurement variations, providing confidence for health policy applications. Most importantly, this study enables Finland to contribute to and benefit from international health literacy research [52], supporting evidence-based strategies and cross-national learning essential to address health information challenges in increasingly complex health context. Future research should link HLS-Q12 scores to external criteria and longitudinal outcomes, and evaluate responsiveness in intervention and policy contexts.

## ETHICS STATEMENT

The studies involving humans were conducted in accordance with the local legislation, institutional requirements, and Finnish national guidelines for ethical review in human sciences. The University of Eastern Finland confirmed that formal ethics committee approval was not required for this study. The participants provided their written informed consent to participate in this study.

## AUTHOR CONTRIBUTIONS

JZ: Material preparation, data analysis, manuscript writing. HR: Methodology discussion, results interpretation, critical review.

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MS: results interpretation, critical review. TM-O: funding acquisition, supervision, conception of the study, results interpretation, critical review. All authors contributed to the article and approved the submitted version.

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## CONFLICT OF INTEREST

The authors declare that they do not have any conflicts of interest.

## GENERATIVE AI STATEMENT

The author(s) declared that generative AI was used in the creation of this manuscript. During the preparation of this work the authors used ChatGPT 5.1 in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.ssph-journal.org/articles/10.3389/ijph.2026.1609337/full#supplementary-material>

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