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Exploring the Measurement Properties of the eHEALS eHealth Literacy Scale among Baby Boomers: A Multinational Test of Measurement Invariance.

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Abstract

Background: The eHealth Literacy Scale, or 'eHEALS', is one of only a few available measurement scales to assess eHealth literacy. Perhaps due to the relative paucity of such measures and the rising importance of eHealth literacy, the eHEALS scale is increasingly a choice for inclusion in a range of studies across different groups, cultures, and nations. However, despite its growing popularity, there have been questions raised over its theoretical foundations and the factorial validity and multi-group measurement properties of the scale are yet to be investigated fully. The current study fills that gap in knowledge.

Objective: This study examines the factorial validity and measurement invariance of the eHEALS scale among Baby Boomers (born between 1946 and 1964) in the US, UK, and New Zealand who had used the Internet to search for health information in the last six months.

Methods: Online questionnaires collected data from a random sample of Baby Boomers from the 3 different countries. The theoretical underpinning to eHEALS comprises social cognitive theory and self-efficacy theory. Close scrutiny of eHEALS with analysis of these theories suggests a three factor structure to be worthy of investigation, which has never before been explored. Structural equation modeling tested a three-factor structure based on the theoretical underpinning to eHEALS, and investigated multi-national measurement invariance of the eHEALS scale.

Results: Responses (n = 996) were collected using random samples from the three countries. Results suggest the eHEALS scale comprises a three factor structure with a measurement model that falls within all relevant fit indices (RMSEA = .041, CFI=.986). Additionally, the scale demonstrates metric invariance (RMSEA = .040, CFI=.984, Δ CFI=.002) and even scalar invariance (RMSEA = .042, CFI=.978, Δ CFI=.008).

Conclusions: This is the first study to demonstrate multi-group factorial equivalence of the eHEALS scale, and does so using three diverse nations and random samples drawn from an increasingly important cohort. The results give increased confidence to researchers using the scale in a range of eHealth assessment applications from primary care to health promotions.

Keywords: Health literacy; eHealth literacy; eHEALS; Baby Boomers; Health Information; Measurement Invariance

Introduction

The importance of health literacy for health status is well recognized. The American Medical Association found health literacy has a stronger impact on health status than a number of sociodemographic variables [1], and is crucial in empowering patients to play a more active role in their own healthcare [2, 91, 94]. The Alliance for Health and the Future describes health literacy as an essential life skill for individuals, a public health imperative, an essential part of social capital, and a critical economic issue [3].

Health information is one of the most frequently sought topics on the Internet [4-5, 92] hence electronic health resources are becoming increasingly vital in terms of overall health literacy

[6, 95]. New technologies that open up a myriad of eHealth applications and communications channels are revolutionizing the ways in which health information is accessed and used by both providers and patients, promising enhancement of quality of care [7] and marking a shift as patients convert from passive recipients to active consumers [5]. eHealth literacy, which is "the use of emerging information and communication technology, especially the Internet, to improve or enable health and health care" [8, p.267], is therefore a crucial area of study in order to understand and enhance the ways in which patients access and use eHealth information.

One measurement tool currently receiving increasing attention is the eHealth Literacy Scale, or eHEALS [9]. A recent systematic review of eHealth literacy measures found forty five of the fifty three published articles used eHEALS [102], illustrating the fact that it is rapidly becoming the accepted standard way to measure eHealth literacy. Despite this widespread use, the eHealth literacy construct and its psychometric properties remain understudied [13-14, 93], leading to the conclusion that "limited empirical evidence exists on the reliability and construct validity of health literacy measures. This raises uncertainty about the accuracy of data being produced in relation to health literacy levels at an individual and population level" [15, p.367].

A further noteworthy omission from current knowledge pertaining to eHEALS is the lack of established measurement invariance. Measurement invariance, which simply means equivalence of measures, is a prerequisite before making any meaningful comparisons between different groups [48]. Too often researchers assume that an instrument developed for one culture or population automatically measures the same construct across another culture or population. However, without the establishment of measurement invariance, group comparisons are not valid or meaningful [103]. Hence it is crucial for any scale used extensively across different nations, cultures, and groups, to demonstrate measurement invariance. Developed in Canada, the scale has since been used extensively in studies with very different samples and in different cultures, including North America [10], Europe [11], and Asia [12].

Ebbinghaus [56] contends that nation-state formation, international co-operation, and ease of availability of data has resulted in some countries being over (or indeed under) represented in many analyses. Consequently, research conducted in one country (usually a North American country) is assumed to be relevant to other countries, irrespective of differences in cultural and social forces. This study is part of a larger piece of research into eHealth in the US, the UK, and New Zealand (NZ). The choice of countries emerged from consideration of their very different rankings on healthcare system performance and their systems of healthcare provision, in the expectation that patients experiencing these different levels of services, choice, and standards would have different eHealth behaviors. Using the Commonwealth Fund [57] ranking system, which comprises major performance indicators on multiple health care dimensions, the UK was an obvious choice as it ranks first overall. While there are still major crisis points with the UK National Health Service [58-59] nevertheless the UK is ranked first across eight of the eleven performance areas, including all of the quality of care indicators and the efficiency indicator. At the other extreme, ranking bottom overall, is the US. The US differs most notably from other industrialized nations because of its lack of universal health coverage, but also ranks behind most other countries on key performance indicators pertaining to health outcomes, quality of care, and efficiency of healthcare delivery. Between these two extremes lies NZ, a country where residents benefit from a public health system that is free or low cost due to heavy Government subsidies [108], and where performance rankings range from high for health measures such as effective care and coordinated care, but lags behind many other countries in safety and equity. Notably, NZ is a country where eHEALS has never before been utilized. Hence, the inclusion of such disparate nations in the current study is an important contribution to knowledge. Table 1 provides the rankings for each country against the major dimensions and sub-dimensions of health care provision provided by the Commonwealth Fund [57].

Table 1. Commonwealth Fund rankings of health care provision by country.

	NZ	UK	US
Quality care	4	1	5
Effective care	2	1	3
Safe care	9	1	7
Co-ordinated care	2	1	6
Patient-centered care	6	1	4
Access	7	1	9
Cost-related problems	6	1	11
Timeliness of care	6	3	5
Efficiency	3	1	11
Equity	10	2	1
Healthy lives	9	10	11
Health expenditure per capita	$3182	$3405	$8508
Overall Ranking	7	1	11

While the three countries selected are vastly different in terms of the health care rankings, they are all Western countries in which cultures may not differ to the extent that perhaps Eastern and Western nations may. Nevertheless, comparison between the three countries on the major dimensions of national culture [115] reveal that while there are some similarities, there are also notable differences, not least in terms of long term orientation, a cultural dimension which measures short-termism and quick solutions over preparing for the future.

This dimension seems particularly important in terms of healthcare planning for future generations.

Baby Boomers (born between 1946 and 1964) are the focus of the current study. Projections suggest that this cohort will place major strains on healthcare systems in each of these chosen nations [60- 62]. Rapid population aging and a steady increase in human longevity is leading to one of the greatest social, economic, and political transformations of all time [63]. Globally, life expectancy has increased by almost 20 years over five decades, and the profundity of this demographic change impacts many economic and social areas, including healthcare. As longevity increases, age-related diseases such as dementia, cardiovascular disease, arthritis, osteoporosis, and type 2 diabetes will place greater demands on healthcare providers. Hence, in an increasingly technology-driven society, eHealth literacy is a crucially important area of study [30, 64]. Many Baby Boomers are both technologically proficient and increasingly taking a greater role in their own healthcare [65]. Indeed, Baby Boomers have a marked difference in social attitudes in comparison with the generation that preceded them, with very different attitudes expressed in certain consumption choices, including bodily maintenance, diet and exercise [66].

However, statistics show that Baby Boomers are not particularly healthy. In comparison to previous generations, there is a higher prevalence of obesity, alcohol consumption, hypertension, and diabetes among Baby Boomers in the US [67], the vast majority of British Boomers have at least one medical condition requiring regular medical care, with only one in six being condition free [68], and few doubt the significant impact that aging is predicted to have on the New Zealand's healthcare expenditure [69]. Interestingly, the three countries under study are bottom of the league in terms of healthy lives (table 1). One of the performance indicators for healthy lives is healthy life expectancy at age 60, and while individual ranking data for this indicator is not provided, it nevertheless gives an insight into the health-related conditions facing the baby boomers under study.

The study presented here therefore addresses two important issues. First, it answers the call for further research to examine the eHEALS scale, and does this through the use of structural equation modelling to examine its underlying structure. Then, by establishing full measurement invariance, validates eHEALS using samples of Baby Boomers (born 1946 to 1964) selected from the US, the UK, and NZ. The paper begins with a brief overview of the eHEALS scale and then synthesizes the diverse studies which have utilized the scale. It then argues for the need to establish measurement invariance, before detailing the procedures used to obtain it across these diverse nations. The paper concludes with a discussion of the implications for future research and practice.

The eHEALS Scale

Norman and Skinner [16] developed the 'lily model' of eHealth literacy. The lily model depicts six core skills or literacies, each represented by an overlapping lily petal that feeds the pistil which is eHealth literacy. These six core skills comprise two components. Table 2 outlines this classification of components and provides an overview of each of the core skills.

Table 2: Components of eHealth literacy lily model

Analytic Components: involving skills applicable to a broad range of information sources and contexts	
Traditional Literacy	Ability to read text, understand written passages, and speak and write a language coherently
Information Literacy	Understand how information is organised on the Internet, how to search for it, and how to use it
Media Literacy	Ability to place information in a social and political context so as to understand how different media forms can shape the conveyed message
Context-specific Components: situation-specific skills	
Computer Literacy	Ability to use computers to solve problems
Science Literacy	Ability to place health research findings in an appropriate context, thus understanding the research processes involved in knowledge creation
Health Literacy	Ability to read, understand, and act on health information

Shortly after disseminating the lily model of eHealth literacy, Norman and Skinner [9] published the eHEALS scale, which comprises eight items designed to "measure consumers' combined knowledge, comfort, and perceived skills at finding, evaluating, and applying electronic health information to health problems" [p.1]. Norman and Skinner [9] report sound scale development procedures, describing a process whereby the six core skills depicted in their lily model were used to compile an initial pool of items from which "an iterative process of item reduction was used to create an instrument that could be easily deployed within a variety of settings and contexts" [p. 3]. This iterative process of item reduction and modification comprised reviews by faculty colleagues, a consumer group with developing literacy skills, and a large pilot test, resulting in the 8-item eHEALS scale shown in table 3.

Table 3: eHEALS scale items

1	**I know what** health resources are available on the Internet
2	**I know where** to find helpful health resources on the Internet
3	I know **how** to find helpful health resources on the Internet
4	I know **how** to use the Internet to answer my questions about health
5	I know **how** to use the health information I find on the Internet to help me
6	I have the skills I need to **evaluate** the health resources I find on the Internet
7	**I can tell high quality health resources from low quality** health resources on the Internet
8	**I feel confident in using information** from the Internet to make health decisions

Even from a cursory glance at the scale it is clear that each item does not relate solely to one skills dimension. Rather, though it is not explicit either in the items themselves or in the published scale development paper [9], it seems that embedded into each item are several core literacy skills. Item 1 'I know what health resources are available on the Internet' is perhaps reflecting traditional and computer literacy, while item 7 could incorporate traditional, information, media, science, and health literacies. It is important to note that Norman and Skinner [9] do point out that the eHEALS scale does not measure the skills directly, but rather is a "measure of consumer's perceived skills and comfort with eHealth" [p. 5].

Developed and used in further studies in Canada [17-18], the eHEALS scale has since been utilized in many countries and cultures across the globe, including the USA [19-30], Australia [98], Germany [31], Greece [101], Israel [32], Indonesia [33], Japan [34], The Netherlands [35-36], Norway [37], Portugal [38], Switzerland and Italy [11], Singapore [12], South Korea [39], Taiwan [40-41], and is currently being used in an ongoing health intervention study in the UK [42]though results from this latter study are not yet available.

The eHEALS scale has also been used with a wide variety of samples, including schoolchildren and adolescents [9, 20, 27, 31, 38, 40-41], parents [23, 100], university students [12, 17], adults comprising different age groups of a wide age range [14, 32, 34],and comprising solely older generations [18, 29-30], as well as veterans [21, 97], patients [19, 24-26, 28, 43], carers [22], and health service providers [10, 33]. The scale has been used with very small (< 100) sample sizes [17-18, 20, 30, 33] as well as studies comprising several thousand respondents [23, 32, 34, 40]. Researchers have found eHEALS to be useful for measuring perceptions of eHealth literacy in order to ascertain skills and training gaps [17] and to measure the success of intervention studies [28, 30, 42]. The scale has also been beneficial in explaining willingness to adopt personal health record technology [26]. Perhaps even more importantly, though the scale measures self-perceptions of eHealth literacy, higher scores on the scale have indicated good health behaviors, including the likelihood of undergoing cancer screening [34] as well as eating a balanced diet and taking physical exercise [99].

Clearly, eHEALS is becoming an established and well-accepted scale with which to measure eHealth literacy, utilized across very different studies with a wide range of research questions and a great deal of diversity in terms of sample profiles. However, often the scale is used without due consideration of its validity and reliability. It has been noted that the eHEALS construct does not appear to fully reflect the six different types of health literacy [15], the representativeness of the results from smaller studies has been questioned [44], and previous authors have noted that the validity of eHealth literacy in general [45], and the eHEALS instrument in particular [36] require further study. Moreover, the original scale authors do note that the eHealth lily model has its roots in social cognitive theory and self-efficacy theory [16]. However, despite their claim that detailed descriptions of these theories appear in their earlier publication [9], there is no explicit mention of these theories or how they were used to develop neither their eHealth literacy definition nor their eHEALS measurement instrument.

Validity & Reliability of eHEALS

Much of the burgeoning research that uses the eHEALS scale does so without consideration of the factorial validity of the construct. Of those studies that do examine the measurement properties of the instrument, most use Principal Components factor analysis [9, 25, 29, 41]. Recently, one study examined the construct validity of eHEALS by first using an exploratory components analysis, which extracted one factor from two different convenience samples. Analysis then turned to further scrutiny of the scale using the Rasch Model, which, in addition to providing details about the perceived difficulty of items, provides reliability statistics to estimate how well an instrument separates individuals on the construct. The study concluded that “eHEALS is a reliable and consistent measurement tool for perceived measurement of eHealth literacy. An exploratory factor analysis showed that items loaded on a single factor solution, thereby supporting the criterion of unidimensionality” [109, p. 11].

However, while exploratory factor analysis such as Principal Components analysis (PCA) is very useful for reducing a large number of items to a more manageable amount, a “confirmatory factor analysis (CFA) of a multiple-indicator measurement model…affords a more rigorous evaluation of unidimensionality according to the constraints imposed by internal and external consistency” [46, p.189]. Only two known studies have used the more complex and sophisticated structural equation modelling in order to construct a CFA of the eHEALS scale. The first, conducted in Japan, entailed translation of eHEALS into Japanese

[34, 47] with CFA used to build a good fitting model comprising a single factor. The second, a German study [31], compared a single factor model to a two-factor model. Of the two German alternatives, the two-factor model was a superior fit, suggesting that the eHEALS scale is not unidimensional, as claimed in much previous literature, most of which has tended to use PCA. However, as these authors themselves admit, the results of the two-factor model clearly still did not indicate a well-fitting model, because several important indices "indicated a poor model fit" [p. 33]. Indeed, even in the better fitting model, the RMSEA was greater than 1.0, which is indicative of a poor fitting model [74-75], while the CFI of 0.914 and the TLI of 0.874 are clearly not close to the .95 needed for a well-fitting model [76].

Noteworthy is the fact that in each of the studies that utilized CFA, eHEALS was translated into a different language from the English in which it was originally designed. When translated, scale items can take on different meanings, and these nuances can impact perceived meanings for respondents [104-105]. The majority of health information on the web is not only in English but developed from an English as first language cultural perspective, and the ramifications of this appear to be far greater than for English speakers of different ethnic origins [106]. Indeed, in their original presentation of the Lily Model [16] Norman and Skinner comment on the fact that the overwhelming content of the Web is in English and suggest that English speakers are therefore not only more likely to find eHealth resources that are relevant to their needs, but are also more likely to find eHealth resources that they can understand. Undoubtedly, then, more research needs to examine the unidimensionality of eHEALS in an English language context.

Importantly, no known previous study has examined the measurement properties of eHEALS in terms of its use with multi-groups. In order to make comparisons between groups, measurement invariance needs to be established. Measurement invariance, or measurement equivalence, is a check to establish that a scale measures the same trait dimension, in the same way, when administered to two different groups [107]. Measurement invariance therefore checks that different groups (based on gender, ethnicity, nationality, or any other individual differences) respond to a measurement instrument in similar ways. Too often, researchers make assumptions about measurement equivalence, yet violations of measurement equivalence threaten fundamental interpretations of results [108]. Hence, measurement invariance is essential for testing theory successfully in different cultural settings [48]. Without such evidence, findings "are at best ambiguous and at worst erroneous" [49, p.78]. A standard scale, particularly one that exhibits measurement invariance, is a potentially valuable research tool for comparative and longitudinal research purposes in a variety of nations in order to create new theories and or test existing hypotheses [50].

There is a growing body of international research that focuses on identifying the antecedents and impact on behavior of the eHEALS scale. Previous studies have examined the correlates of eHEALS in terms of antecedents such as sociodemographic characteristics [19, 64], living arrangements [19], medical conditions and health status [19, 64], and frequency of internet use [19]. Additionally, some studies have attempted to measure behavioral correlates, for example eHEALS has been described as a marker for consuming more information [51], basic Internet use [36] and using the Internet specifically for healthcare and lifestyle information [12, 14, 40], predicting post medical visit online health information seeking [24], patient willingness to adopt a personal health record [26], and the likelihood of undergoing cancer screening [34]. There are also a growing number of studies that make comparisons between groups. For example, past research has made direct comparisons of eHEALS scores between different groups on the basis of various sociodemographic variables [19, 38, 40], and users and non-users of Web 2.0 for health information [64]. Research has also used eHEALS to identify groups with low and high eHealth literacy and made behavioral comparisons based on these groups [11]. Establishment of measurement invariance of the scale would be a useful contribution to knowledge because measurement invariance is needed to ensure group comparisons are valid and meaningful [103]. Such groups can comprise any distinguishing measure, so in order to make a comparison of say males and females drawn from the same population, measurement invariance of a scale should be checked. This research makes that contribution.

CFA models should test a hypothesis based on a strong theoretical and/or empirical foundation [52]. As previously discussed, from a theoretical perspective, close scrutiny of the health literacies that make up the lily model (table 2) and the eight eHEALS scale Items (table 3) clearly shows that eHEALS does not reflect the six core skills depicted in the lily model. Indeed, this observation appears in previous literatures [31]. Hence it is not easily apparent how to decide on the number of factors to test in a model based solely on the items in the lily model from where Norman and Skinner [9] claim eHEALS emerged. Norman and Skinner do however claim that the "foundations of the eHealth literacy concept are based in part on social cognitive theory and self-efficacy theory which promote competencies and confidence as precursors to behavior change and skill development" [9, p. 2]. It should be noted, however, that though their assertion that these theories are described in detail in their paper published that same year [16], this claim does appear to be an overstatement, as there is in fact very little detail pertaining to these theories explicitly in their published work. What these authors do, however, is explain that eHEALS is based on the premise that the core skills or literacies in the lily model (table 2) are not static, and can be improved with intervention and training. In fact they explain that literacy is as much a process as it is an outcome. It is here that Social Cognitive Theory (SCT) is apparent in their work, as SCT is based on a model of causation where behavior, environmental influences, and personal factors (which include cognitive, affective, and biological factors) all interact and influence each other [53]. Hence rather than the lily model, the underlying theories to eHEALS, namely SCT and self-efficacy theory [16], are used here to attempt to develop a hypothesis upon which a measurement model can be tested.

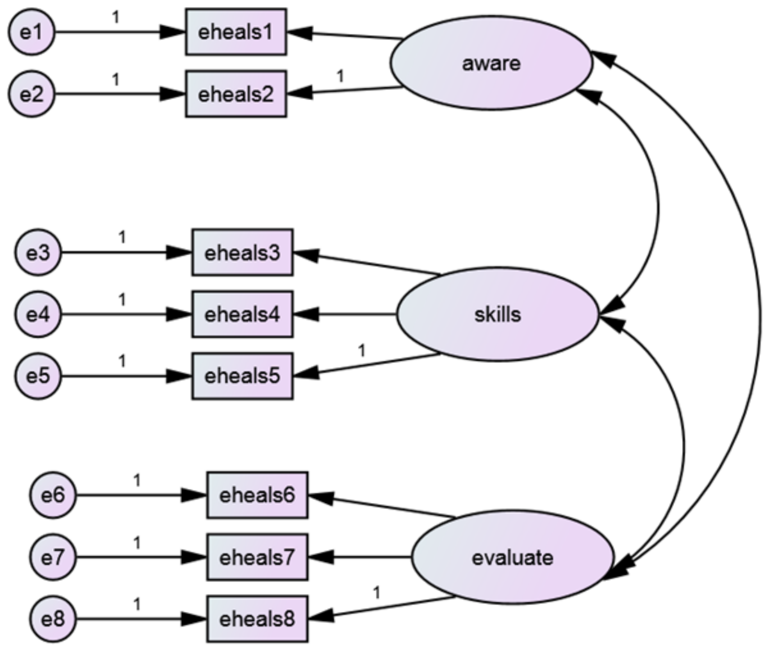
The root of SCT is the concept of reciprocal determinism, where three factors – person, environment, and behavior – are interlinked [53]. The individual learns from experiences and the environment, which incorporates external social contexts. Responses to this learning and the environment affect the individual's behavior and therefore their ability to achieve goals. As Bandura [54] stresses, diversity in psychobiological origins, experiential conditions, and behavior results in substantial individual differences in what individuals can and cannot do. This theory therefore makes perfect sense as a foundation to eHEALS, given that individuals differ greatly in their competences pertaining to the literacies depicted in the lily model.

It is clear that eHEALS measures an individual's perceived skills as opposed to actual skills. An important influence in the personal dimension of the reciprocal model of SCT is self-efficacy, as this can directly influence self-motivation. Self-efficacy relates to self-belief and confidence: hence, self-efficacy is not to do with the skills a person has, but rather what that person believes they can achieve with those skills. Self-doubt and negativity can lead to failure, while self-belief and confidence can lead to an increase in effort and persistence until success is realized. Hence self-efficacy can lead to restructuring of goals, including either lowering standards or setting higher goals in order to achieve even greater things, all based on the individual's perceived capabilities [54].

Attempting to apply these theories to the eHEALS scale is not straightforward at first glance. Nevertheless is relatively easy to identify those items that relate to self-efficacy. Items 6 ("I have the skills I need to evaluate…"), 7 ("I can tell high quality….from low quality…"), and 8 ("I feel confident in using…) all appear to pertain to a belief and confidence in one's own evaluation skills in order to effectively use health resources and information. However, keeping in mind that some previous empirical evidence suggests eHEALS is neither a single factor structure nor a two-factor structure [31], the remaining items require close scrutiny in order to identify potential groupings. This close scrutiny reveals a difference between items 1 and 2, which both pertain to an awareness of what resources and information are available on the internet, and Items 3-5 which all pertain to the "how" in terms of how to find and how to use these resources. In other words, items 1 and 2 relate to an awareness of Internet health resources, items 3-5 to the skills needed to access them, and items 6-8 to the self-belief that one can effectively evaluate them.

These three groupings do, in fact, relate to SCT in that social and technological changes impact life experiences to different degrees among different individuals [53]. Hence, knowledge of such social and technological innovations (various levels of awareness and learning about health resources on the Internet), which are reflected in items 1 and 2 of the scale, are clearly influenced by environmental factors which impact exposure to different sources of information pertaining to Internet health resources. Then, the skills needed to access these Internet health resources, which comprise items 3-5, are impacted by modelling, instruction, and social persuasion in the environment. Clearly there is a behavioral element here, and such skills are a response to the environmental stimuli as well as being impacted by personal factors such as internal dispositions, motivation, and biological properties that impose constraints on capabilities. This reciprocity is a key aspect of SCT theory [111]. Finally, self-efficacy is clearly apparent in the remaining items (items 6-8) as these items reflect an individual's self-perception of the skills needed to fully utilize the eHealth information attained on the Internet. Of course, the individual's environment and previously learned knowledge will influence the levels of self-belief that the individual holds, which is in line with the reciprocal nature of SCT theory. Figure 1 shows the resulting three-factor model to be tested. Factor 1 pertains to awareness (knowledge of what resources are available and where they are), factor 2 to the skills and behavior needed to access them, and factor 3 to believing one has the ability to evaluate them once accessed.

Figure 1: Three-Factor Model



Methods

Instrument

The original eHEALS scale was developed at a time before the rise of social media [6]. Extensive social networking opportunities, as well as advances in technology such as Web 2.0, change the landscape in terms of how consumers interact with health information [55]. Hence, the wording of the original scale items was tweaked in order to incorporate ‘health information’ as well as ‘health resources’. This is because it was felt that solely using the term ‘resources’ may limit eHealth information search to official resource sites (e.g., the American Cancer society, Cancer Research in the UK, or Cancer Society NZ) and not incorporate the increasingly important electronic word-of-mouth that occurs on social media sites and online forums. Norman [6] advocated that the scale may need to be adapted, suggesting a social media sub-scale could perhaps enhance the current scale, while others have suggested that interactive applications would indeed enhance the eHEALS scale [96]. For these reasons, the words “and information” to several items were added. Informal feedback among friends, family, and colleagues when they were asked to name some “Internet health resources and information” reflected a wide perspective, in that people immediately cited search engines (usually Google) but also cited a wide variety of other sources including online forums and Facebook support groups. For example one person who was at the time undergoing tests for multiple sclerosis, replied that he had not only studied the Multiple Sclerosis Society’s web pages and viewed this as an important health resource had also joined a Facebook group to learn more about how people coped with their diagnosis and viewed this as an informal information resource. Hence rather than drastically change the scale by adding items specific to social media, it is hoped that information gained from social media is now incorporated. Table 4 shows the adapted scale. Approval was granted by the Universities ethics committees.

Table 4: Adapted eHEALS scale

1	I know what health resources and information are available on the Internet
2	I know where to find helpful health resources and information on the Internet
3	I know how to find helpful health resources and information on the Internet
4	I know how to use the Internet to answer my questions about health
5	I know how to use the health information I find on the Internet to help me
6	I have the skills I need to evaluate the health resources and information I find on the Internet
7	I can tell high quality health resources and information from low quality health resources and information on the Internet
8	I feel confident in using information from the Internet to make health decisions

In addition to the tweaked eHEALS scale, because the study is part of a larger piece of research into eHealth, the survey contained questions pertaining to information search and usage such as sources of health information used (including interpersonal sources such as friends and family as well as formal health information sources such as non-profit organizations and health care providers), perceived advantages of using Internet eHealth sources (e.g., 24-hour accessibility, convenience, anonymity, etc.), and perceived usefulness of Internet eHealth resources in comparison to information provided by health care providers (Likert-type scale ranging from 'much less useful' to 'much more useful'). In addition the questionnaire contained a battery of sociodemographic variables, including age (measured via year of birth), gender (male or female), marital/relationship status (married, widowed, divorced, separated, in a domestic partnership or civil union, single, but cohabiting with a significant other, single, never married), work status (employed full-time, employed part-time, retired, unemployed, homemaker, on government/state benefit, student/in training, other: please specify), and educational attainment (University degree, Vocational training e.g., trade apprenticeship, Professional qualification, College qualification, High school, Less than High school).

Sample

In each country, a commercial organization was commissioned to survey randomly-selected Baby Boomers. A prerequisite for completing the survey was that respondents 1) had to be born between 1946 and 1964 and 2) had used the Internet to search for health information in the last six months. Each organization was instructed to collect data from at least 250 Baby Boomers, and therefore the first respondents were included in the survey before the survey was closed, hence the surveys were open for less than two days in each country. Prior to completing the survey, respondents were informed of its purpose (an international research project studying the use of the Internet to search for and share health information) its academic nature, how the data would be stored (password protected secure University drives) and for how long, and the length of the survey, which typically took 20 minutes to complete. This procedure resulted in 996 usable questionnaires. There was no missing data as a "not-applicable" option was given to suitable questions, and while respondents were able to review and change their answers they were unable to submit incomplete questionnaires.

Data Analysis

In order to further check the psychometric properties of the eHEALS scale, a series of confirmatory factor analyses (CFA) using AMOS 20 were conducted. Standard global model fit indices with well-known fit guidelines were used. Hence the RMSEA (root mean square error of approximation), which is a popular measure of fit in structural equation modelling (SEM) and is now recognized as one of the most informative criteria in SEM [77] was utilized. The guidelines suggested by Hu and Bentler [76] were adhered to, hence RMSEA values of .00 to .05 indicate a close or good fit, .05 to .08 a fair fit, .08 to .10 a mediocre fit, and over .10 a poor fit. Other fit indices which were used to assess the models were the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), both of which should be close to .95 [76]. AIC (Akaike's Information Criterion) is a fit statistic used to compare two or models, with smaller values indicating better fit [110].

Additionally, PCLOSE was used to test the hypothesis that that RMSEA is good in the population, testing the null hypothesis that RMSEA is no greater than .05 [77]. In other words, PCLOSE is an additional test of model fit and this result indicates a close fit. Data analysis also included the use of Hoelter's Critical N, which is another fit statistic that differs from the others used here in that it focuses directly on the adequacy of the sample size, rather than the fit of the model. A "value in excess of 200 is indicative of a model that adequately represents the sample data" [77, p. 83].

Steenkamp and Baumgartner [49] contend that multi-group confirmatory factor analysis is the most powerful and versatile approach to testing for cross-national invariance and offer a sequential testing procedure for doing so. This procedure was followed here. Measurement invariance comprises three levels: configural, metric, and scalar. Each level is an increasingly stringent test of multi-group invariance. Consequently, a multi-group measurement model was constructed and tested first for configural invariance, which provided a baseline model for comparisons of subsequent tests for invariance. Testing the pattern of salient (non-zero) and nonsalient (zero or near zero) loadings defined the structure of the measurement instrument [49]. In other words, the purpose of the test of configural invariance was to explore the basic structure of the construct, and check that participants from different groups conceptualized the constructs in the same way [103]. Simply put, did respondents, irrespective of their cultural or national heritage, employ the same conceptual framework [87] when answering the questions that make up the eHEALS scale?

Configural invariance does not, however, mean that the respondents in different nations reacted to the scale items in the same way. In order to compare item scores meaningfully across nations, and thus have confidence in observed item differences being indicative of cross-national differences in the underlying construct, metric invariance is required. Indeed, for a scale to be useful in larger studies which examine structural relationships with other constructs cross-nationally, metric invariance is needed. [49]. Metric invariance checks that the scale is measured in the same way across groups, in that not only do different groups respond to scale items in the same way, but also that the strength of the relations between items and their underlying construct is the same across groups [103].

In practice, most researchers focus on the two preceding and most fundamental steps, which are tests of configural and metric invariance [80]. There may be some projects, however, where researchers want to compare means and in order to do this the scale needs to exhibit scalar invariance. Scalar invariance implies that cross-national differences in the means of the observed items are due to differences in the means of the underlying constructs [49, 82], and therefore indicates that the latent means can be meaningfully compared across groups [103]. Scalar invariance tests whether, in addition to the factor loadings, the intercepts are the also the same, which implies that cross-national differences in the means of the observed items are due to differences in the means of the underlying constructs [82].

Results

Preliminary Analysis

Table 5 provides a profile of the sample by country.

Table 5. Sample profile by country

	UK	NZ	US	Total
N=				
	407	276	313	996
Gender (%)				
Male	47	51	52	50
Female	53	49	48	50
Mean Age				
Years	59.6	61.3	60.3	60.3
(SD)	(5.15)	(5.78)	(5.35)	(5.43)
Work Status (%)				
Working Full Time	32.4	29.7	26.8	29.9
Working Part Time	15.5	19.6	10.2	15.0
Retired	31.9	24.3	36.4	31.2
Unemployed/Welfare	8.6	15.2	8.6	10.4
Homemaker	8.6	4.3	6.4	6.7
Other	2.9	6.9	11.5	6.7
Education				
Less than high school	0.5	0.0	2.6	1.2
High school	38.6	32.2	18.8	30.6
College/practical/technical/occupational	36.4	36.6	32.3	35.1
University degree	24.1	31.2	46.3	33.0

Table 6 provides the mean eHEALS Item scores by country. While the purpose of this paper is not to compare the countries in question in terms of eHealth literacy (that will be done elsewhere), noteworthy is that even a cursory glance at table 6 reveals American respondents had higher scores than their NZ and UK counterparts. Whether or not this is due to the overall higher educational attainment of the US sample (table 5), perceptions of poorer health care provision (table 1) or other reasons is currently unknown. Across all three countries, the corrected item-total correlations revealed no low values (all were above .635) and it was not possible to obtain a higher alpha score by deleting any item. In all three nations, Cronbach alpha results were very high (UK = .931, US = .917, NZ =. 910). Indeed, with medical researchers being urged to be more critical when reporting alpha values [70] it is noted that alphas this high (> 0.90) may suggest redundancies or that the construct being measured is too specific [71]. Hence, analysis turned to further investigation using confirmatory factor analysis.

Table 6: Mean eHEALS item scores by country

Item	**US**		**UK**		**NZ**	
	M	***SD***	***M***	***SD***	***M***	***SD***
1	3.81	.76	3.67	.77	3.56	.81
2	3.91	.71	3.78	.71	3.70	.77
3	4.01	.68	3.80	.71	3.88	.66
4	3.96	.77	3.83	.72	3.81	.68
5	3.89	.73	3.71	.74	3.73	.70
6	3.62	.94	3.47	.82	3.37	.93
7	3.61	.85	3.48	.87	3.28	.93
8	3.66	.79	3.50	.88	3.39	.94
Cronbach's α	.917		.931		.910	

Confirmatory Factor Analysis

The first step in testing for discriminant validity of a model structure with multiple latent factors is to reject the possibility of a single factor structure [73]. Table 7 details these single-factor CFA results.

Table 7. eHEALS CFA by nation – single factor structure

Nation	N	X^2	df	*P*	RMSEA	P close	AIC	CFI	TLI
UK	407	379.003	20	<.001	.210	<.001	411.003	.864	.809
NZ	276	263.140	20	<.001	.210	<.001	295.140	.833	.767
US	313	199.218	20	<.001	.169	<.001	231.218	.896	.854

The data do not fit the one-dimensional model well. In addition to significant chi-square values (UK: X^2 = 379.003, df = 20, P < .001; NZ: X^2 =263.140, df = 20, P < .001; US: X^2 =199.218, df = 20, P < .001) the RMSEA values of .210 for UK and NZ and .169 for US fell outside the guidelines [74-75] that propose values less than .05 indicate good fit, values ranging from .05 to .08 reflect reasonable fit, values between .08 and .10 indicate mediocre fit, while values greater than .10 reflect poor fit. Likewise the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) should be close to .95 [76], yet fell well below the cut-off point suggested for these indices in all three nations.

Analysis then turned to examination of the hypothesized three-factor model, using the UK data. Testing for factorial equivalence encompasses a series of hierarchical steps that begins with the determination of a baseline model for each group separately [77]. The first step, then, was to establish a baseline model from one of the samples. The UK data were chosen simply because the UK sample comprises the largest number of respondents. While the three-factor model revealed a much better fit to the one-dimensional model, examination of the modification indices suggested improvement through the pairing of error terms associated with eHEALS Items 2 and 3. One possible method effect that can trigger error covariance is a high degree of overlap in item content [77]. The high Chronbach alpha scores presented in Table 6 do of course suggest such redundancy [71]. Scrutiny of Items 2 and 3 did reveal a degree of overlap, in that Item 2 asks respondents if they know where to find resources while Item 3 asks them if they know how to find these resources. Clearly, to some people, there is not much difference in the meaning of these questions. Given the apparent overlap in the content of these items, and the high Chronbach alphas which had already suggested some redundancy between scale items, the three-factor model was respecified to include these correlated errors, and analysis moved from confirmatory to exploratory mode.

Table 8. eHEALS CFA – respecified three factor structure (UK data)

N	X^2	**df**	***P***	**RMSEA**	**AIC**	**CFI**	**TLI**
407	44.174	16	<.001	.066	84.174	.989	.981

As can be seen from Table 8 the RMSEA of .066 was within the range for a reasonable fitting model, the CFI of .989 and the TLI of .981 far exceeded the recommended minimum values of .95 and the AIC of 84.174 shows a dramatic improvement on the previous model. Examination of the standardized residuals revealed none to exceed the threshold of 2.58 [79]; indeed the highest standardized residual was 1.102 between eHEALS5 and eHEALS8, with all other standardized residuals falling below 1. In sum, the respecified three-factor model fitted the UK data well.

Measurement Invariance

For the scale to be useful in multi-national research, measurement equivalence is needed; without evidence of invariance conclusions based on the scale "are at best ambiguous and at worst erroneous" [49, p.78]. The next goal, then, was to examine the basic meaning and structure of the construct cross-nationally, in order to establish whether or not the scale is conceptualized in the same way across countries. Before moving to analysis of multinational invariance, however, Byrne [77] recommends testing the model separately in each group as the first step toward multi-group confirmatory factor analysis. Table 9 gives the goodness of fit indices for each nation (including the UK data for comparative purposes). All samples demonstrated indices falling within the boundaries outlined earlier. Therefore, the model fit was acceptable for all countries.

Table 9. eHEALS CFA by nation – three factor structure

Nation	N	X^2	df	*P*	RMSEA	AIC	CFI	TLI
UK	407	44.174	16	<.001	.066	84.174	.989	.981
NZ	276	40.651	16	.001	.075	80.651	.983	.970
US	313	43.529	16	<.001	.075	83.529	.984	.971

A multi-group measurement model (based on the final 3-factor model) was then constructed and tested first for configural invariance. Table 10 shows the results of this and subsequent analyses. The fit indices of the configural model ($X2$ = 128.363, df = 48, P < .001), RMSEA = .041, CFI = .954, indicate that the model cannot be rejected, which led to the conclusion that the specification of the Items that index the three factors of eHEALS are configurally invariant for the three nations under study.

The results of the metric invariance analysis, when all factor loadings are constrained equal across all three groups, are presented in Table 10. Despite the fact that metric invariance is often difficult to achieve [80], although the chi-square change between the configural and the metric model is non-significant, the ΔCFI of .002 is well below the proposed cut-off point of .01 [81], suggesting that the measurement model is completely invariant. This means result provides strong evidence that the eHEALS scale is ready to use, with a degree of confidence, in the different countries under study.

Indeed, the scale is now ready for exploring and testing structural relationships, which is the most important application for most researchers. Despite the fact that full invariance is often difficult to achieve [80], as shown in table 10 further analyses demonstrated the eHEALS scale to exhibit scalar invariance, hence analysis can include direct comparisons of mean scores. Indeed, both the "excessively stringent" [77, p. 220] test of invariance resulting in a significant value in the change in X2 (74.874, Δdf = 26, P <.001), and the ΔCFI of .008 was below the .01 cut-off point [81]. Hence, despite potential social and/or cultural differences, the scale is unaffected. For each model, the RMSEA closeness of fit (PCLOSE) far exceeds minimum recommended P-value of at least .05 [78], and Hoelter's Critical N at both the .05 and .01 CN values are greater than 200.

Table 10. Measurement invariance of eHEALS across NZ, US, and UK

Model	$\boldsymbol{X}^2$	df	*P*	RMSEA	P CLOSE	Δ $\boldsymbol{X}^2$	Δ df	Sig.	CFI	Δ CFI	Critical N .05	Critical N .01
1) Configural invariance	128.363	48	<.001	.041	.954	N/A	N/A	N/A	.986	N/A	505	571
2) Metric invariance	149.262	58	<.001	.040	.983	20.899	10	.022	.984	.002	512	573
3) Scalar invariance	203.237	74	<.001	.042	.971	74.874	26	.000	.978	.008	466	515

Despite not checking for normality prior to analysis, noteworthy is the fact that the data indicated no departure from normality, as evidenced by no rescaled β2 values exceeding 7 [83]. Table 11 provides these rescaled β2 values. However, there was some suggestion of multivariate kurtosis. Consequently, bootstrapping using 2000 bootstrap samples, none of which was unused, revealed only very small differences between the maximum likelihood-based estimates and the bootstrap-based estimates (table 11). Moreover, no confidence intervals included zero (table 12). Thus, there were no substantial discrepancies between the results of the bootstrap analysis and the original analysis, and the interpretations of the results presented earlier are without fear that departure from multivariate normality has biased the calculation of parameters [84].

Table 11. Rescaled β2 values and differences in ML estimates and bootstrap estimates

Variable	Rescaled β2 values			Differences in ML estimates and bootstrap estimates		
	UK	NZ	US	UK	NZ	US
eHEALS 1	.741	.238	1.415			
eHEALS 2	2.011	1.304	1.850	.008	.013	.007
eHEALS 3	2.110	1.997	2.924			
eHEALS 4	1.986	1.296	2.181	.002	.008	.006
eHEALS 5	1.709	.746	.934	.003	.008	.015
eHEALS 6	.189	.016	.297			
eHEALS 7	.136	-.117	-.063	.005	.001	.012
eHEALS 8	.484	.078	-.085	.005	.002	.013

Table 12. Bias-Corrected bootstrap confidence intervals

Parameter	UK		NZ		US	
	Lower	Upper	Lower	Upper	Lower	Upper
eHEALS 1 < -- aware	.878	1.055	.923	1.203	.921	1.129
eHEALS 2 < -- aware	1.000	1.000	1.000	1.000	1.000	1.000
eHEALS 3 < --- skills	.926	1.083	.792	1.007	.783	.989
eHEALS 4 < --- skills	.928	1.083	.856	1.069	.975	1.129
eHEALS 5 < --- skills	1.000	1.000	1.000	1.000	1.000	1.000
eHEALS 6 < --- evaluate	.862	.995	.874	1.098	1.093	1.448
eHEALS 7 < --- evaluate	.829	.972	.912	1.133	.973	1.283
eHEALS 8 < --- evaluate	1.000	1.000	1.000	1.000	1.000	1.000

Finally, convergent validity was tested. First, inspection of the factor loadings presented in Table 13 revealed that all exceed the ideal of .7 [85]. Moreover, all factor loadings were positive and statistically significant.

Table 13. Standardized regression weights[1]

			UK	NZ	US
eheals2	<---	aware	.919	.846	.912
eheals1	<---	aware	.836	.825	.857
eheals5	<---	skills	.843	.841	.842
eheals4	<---	skills	.877	.857	.867
eheals3	<---	skills	.874	.832	.877
eheals8	<---	evaluate	.843	.837	.818
eheals7	<---	evaluate	.795	.832	.751
eheals6	<---	evaluate	.854	.826	.730

[1]All factor loadings are positive and statistically significant

Additionally, Table 14 presents the average variance extracted (AVE) and the construct reliability (CR) results for each nation. All AVEs exceeded the cut-off of .5 [86] indicating convergent validity and all CRs exceeded .7, again indicating good reliability. Taken together, the evidence provides support for the convergent validity of the 3-construct eHEALS measurement model.

Table 14. Average variances extracted (AVE) and construct reliability (CR)[2]

	UK		NZ		US	
	AVE	**CR**	**AVE**	**CR**	**AVE**	**CR**
Aware	.772	.871	.699	.822	.783	.878
Skills	.748	.898	.711	.881	.743	.897
Evaluate	.691	.870	.691	.871	.589	.811

[2] The AVE and CR are not provided by AMOS software so they were calculated using the following formulae:

$$VE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

λ represents the standardized factor loading and i is the number of items.

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + (\sum_{i=1}^{n} \delta_i)}$$

(δ) represents error variance terms (delta)

Discussion

Healthcare providers and researchers need a valid, reliable, and easy to use measurement tool with which to assess levels of perceived eHealth literacy among different groups of patients. Until now, there has been some debate about the construct validity of the eHEALS scale, and indeed the validity of the measurement of eHealth in general [13-15, 93], casting doubt over subsequent results. Hopefully the current study alleviates some of that doubt.

The finding that eHEALS comprises three distinct factors is novel and important because the factors that emerged are clearly based on the underlying theory on which Norman and Skinner's [16] definition of eHealth literacy is founded. The current study is the first to demonstrate that eHEALS does indeed relate to the Social Cognitive Theory upon which it is founded. Future research should attempt to do the same. Previously, research has not given due attention to the underlying theoretical arguments for unidimensionality versus multidimensionality, with the majority of studies that did examine the factor structure of the scale being limited to PCA [9, 12, 25, 29, 38, 41], rather than CFA which provides a much more rigorous evaluation.

Interestingly, the two studies that have used CFA have examined the scale did so after it was translated into languages other than the one in which it was designed [31, 34, 47]. Given translation problems [104-105], it is possible that language issues have impacted results in other studies. Moreover, in this study the minor tweaks to the scale in terms of insertion of the words 'and information' into five of the items could perhaps have affected respondent's derived meaning. Finally, the use of samples comprising solely Baby Boomers could have impacted results. Of the two previous studies to use CFA, the first used a wide age range [34, 47] and the second used adolescents [31]. Of course, eHEALS was originally designed using 13-21 year olds [9]. Future research should take these issues into account.

As no previous known studies have attempted multi-national measurement invariance of eHEALS, the establishment of full measurement invariance is another novel and important contribution. The results of configural invariance test suggest that the respondents under study employ the same conceptual framework when answering eHEALS, despite their different cultural experiences and indeed very different experiences of healthcare provision. Second, Steenkamp and Baumgartner [49, p.82] note, "When the purpose of the study is to relate the focal construct to other constructs in a nomological net, full or partial metric invariance has to be satisfied." Clearly, the level of measurement invariance required for the purposes of investigating eHealth literacy in a variety of disparate nations is established. Finally, a cursory glance at the mean scores presented in Table 6 suggests that US Baby Boomers are more eHealth literate than their UK and NZ counterparts. While the examination and discussion of such differences is beyond the scope of the current paper, it is nevertheless important to note that such comparisons can now be made legitimately, as scalar invariance has been established. Confidence in the results of such comparisons has increased due to the establishment of full measurement equivalence [88, 89]. Moreover, the average variance extracted and the construct reliability results for each nation all suggest convergent validity and good reliability. Overall, these results provide solid support for the convergent validity of the three-factor eHEALS model.

These findings are also important from a practical perspective. Results demonstrate that, consistent with the theory upon which it was developed, eHEALS assesses self-perceptions of three important and distinct (though interrelated) elements of eHealth literacy: awareness of Internet health resources (items 1 and 2), the skills needed to access them (items 3-5), and the self-belief that one can effectively evaluate them (items 6-8). Hence eHEALS can now be used to segment health consumers into distinct groups based on their scores on the scale, with corresponding intervention and training provision designed around meeting the needs of these segments. Those individuals with relatively low scores on the awareness factor would need to be offered basic training designed to address the rudimentary elements of eHealth in terms of describing and demonstrating the range of appropriate resources available and how they can be found. For people whose scores are relatively low on this factor, such training should perhaps be stand-alone and could be the foundation level training. Once mastered, individuals could be offered the second level training, designed for those people whose scores are relatively low on the skills factor. This skills training should be designed to perhaps build on basic knowledge and concentrate on developing the individual's search and evaluation skills pertaining to eHealth resources. Finally, a third training program could be developed which concentrates on developing and building self-efficacy, in order to give people the self-belief that they are truly empowered patients who are able to play an active role in their own healthcare. Most training and educational programs incorporate levels of progression in their design, and eHealth intervention and training programs should be no different.

Practical intervention and training around eHealth is important for several reasons. EHealth has the potential to assist self-management in consumers with chronic health conditions, and evidence suggests that even in developed countries, half of the population with chronic health conditions have elementary navigational needs and would benefit from basic training in this area [98]. Training programs are crucial because patients with higher levels of health literacy have significantly lower anxiety levels than people with inadequate health literacy, and have fewer and shorter consultations with health care providers [116] hence there are economic benefits to such training programs. Improvements in ability and self-belief to access and use Internet Health resources have knock-on benefits in terms of ability and willingness to use other eHealth resources such as electronic health records, patient portals, and self-management tools [45]. Thus understanding different skills levels and needs are important for policy makers and health care providers who could all use such information to develop correct and targeted interventions for different segments of the population. Indeed, it has even been suggested that eHealth is so important it should be incorporated into school curricula

[101]. When eHEALS was first designed in 2006, Norman and Skinner [9] claimed that the scale has the potential to serve as a means of identifying those who may or may not benefit from referrals to an eHealth intervention or resource. The current research builds on this claim and suggests that eHEALS can be used to ascertain the type of intervention or resource that could benefit these different segments.

Conclusions

The usefulness of a short, easy to administer scale that measures a person's perception of their eHealth literacy is beyond doubt. Indeed, the extensive use of the eHEALS scale across a variety of studies in countries across the globe is testimony to the urgent requirement for such an instrument. The research presented here details a more rigorous investigation of the measurement properties of the eHEALS scale than has previously been conducted, using confirmatory factor analysis rather than principal components analysis. Based on social cognitive theory and self-efficacy theory, a three-factor model was tested and confirmed.

Research often needs to make comparisons across groups or across time and in order to be able to do this, a scale must demonstrate measurement invariance. Only by establishing measurement invariance can there be assurance that comparisons are valid [90]. In other words, establishing measurement invariance provides evidence that score differences across countries are a true representation of differences in the construct under study, rather than differences brought about social and cultural factors or other such confounding variables [87]. This research has demonstrated full measurement invariance of the eHEALS scale among Baby Boomers in three diverse nations, meaning the scale is now ready to use with far more confidence among researchers in these nations. This research has therefore added weight to Norman and Skinner's [9] contention that the scale is a useful addition to a range of eHealth assessments from primary care to health promotions. The identification of three distinct factors not only confirms the theoretical antecedents upon which eHEALS was built, but also suggests that the scale can now be used to better segment consumers and identify different skills gaps, enabling policy makers and healthcare providers to design and offer tailored interventions and training programs to address such gaps.

The study is not without its limitations. While Baby Boomers are a justifiably important sample for health care and eHealth research, the three factor structure that emerged here needs to be investigated using younger samples to ensure that Boomers are not unique and the three factor structure is indeed applicable to all age groups. Second, while the three nations chosen do vary a great deal in terms of health care provision rankings and to a lesser extent on some important cultural dimensions, they are nevertheless all English speaking Western countries. It has been noted that when eHEALS was translated, different factorial structures emerged. It is recommended that the three factor model is tested in very diverse cultures (for example Eastern countries) and among non-English speaking nations. Finally, it is acknowledged that the current version of eHEALS was designed before the rise in social media and Web 2.0 technology. While some attempt has been made to incorporate the interactive nature of today's online environment by tweaking the scale (specifically, adding 'and information' to items), the suggestion that the marginally updated version used here is sufficient to incorporate interactive resources is based solely on anecdotal evidence gained by asking family, friends, and colleagues. It is recommended that a more formal study investigates the way respondents perceive the eHEALS scale in its current form, as it may need to be more extensively altered, or indeed a new scale may need to be designed, in order to fully capture the myriad of interactive eHealth resources that consumers are now able to access.

Over 80% of Baby Boomers in all three countries under study use the Internet regularly [112-114]. Nevertheless, this cohort did not grow up using the Internet, and there may be some for whom knowledge, skills, and self-confidence around eHealth resources still lag behind the levels that perhaps exist among younger cohorts. Yet, the Baby Boomer cohort is crucially important from an eHealth perspective because forecasts predict that it is this cohort that is increasingly going to put major pressures on healthcare systems [60- 62]. Importantly, Bandura [111] explains that personal factors can be altered dramatically to make improvements to the functioning of individuals. Competency can be developed through training and guidance, which in turn can increase self-belief in capability levels. While there are already eHealth training lessons available across all three countries included in the current study, the findings suggest these training programs should be built around knowledge of what health information and resources are available on the Internet, and then developing the skills needed to access them. Motivational enhancements should also be incorporated into such training in order to ensure an enhancement in self-belief.

In sum, the current study fills an important gap in that it provides future researchers and practitioners with more faith in the eHEALS measurement scale than existed previously. The scale can now be used with a degree of confidence in a variety of nations and in studies with a variety of research objectives, including the modeling of complex relationships among variables. The choices of nations and the demographic of the samples therein are also strengths of the study: all too often scale evaluation and development comprises young (often student and often US) samples. Studies often use scales developed in a different country or culture without checking that the measure is equivalent. This study has demonstrated that eHEALS can be used with confidence across a variety of nations and cultures. This study therefore lends support for the contention that eHEALS is a valid scale with which to measure self-perceptions of eHealth literacy, a concept that is set to become even more important in the future.

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