Promoting healthy eating in Iran: The roles of information-seeking ability and e-health literacy in the digital age

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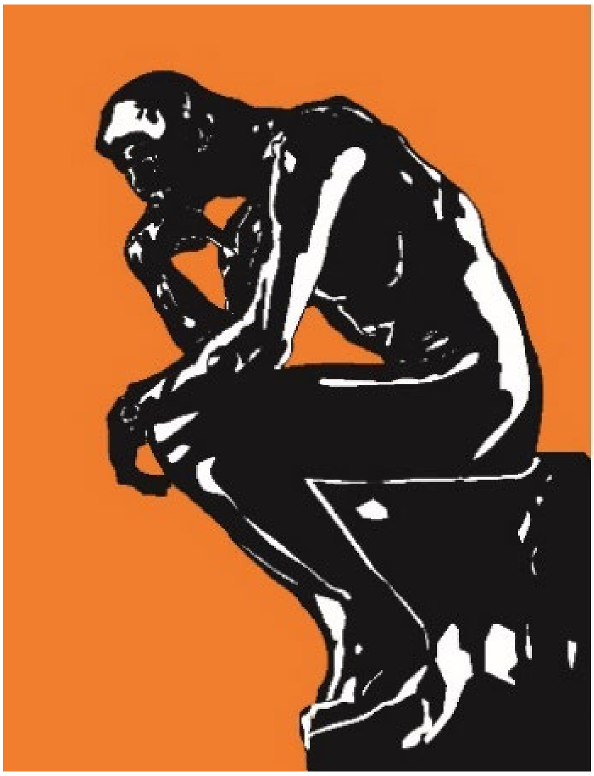

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"Innovation can help Kingfisher conserve energy while maintaining a sense of tranquility, which is suitable for an increasingly advanced age with diminishing physical strength."

—In "Innovation"; *Wild Wise Weird* (2024)

Abstract

Healthy eating has long been a focus of professionals and researchers, both to evaluate strategies for improvement and to gain a deeper understanding of its dynamics in order to develop effective promotion methods. This study aims to examine the roles of individuals' information-seeking abilities and e-health literacy in fostering a healthy eating intention among Iranians. Employing Bayesian Mindsponge Framework analytics on a dataset of 9,755 Iranian participants, the study found positive associations between healthy eating information-seeking ability, e-health literacy, and healthy eating intention among Iranian adults. However, the moderating effect of e-health literacy on the relationship between information-seeking ability and healthy eating intention remains ambiguous. We suggest that enhancing individuals' healthy eating information-seeking abilities and e-health literacy, alongside improving the availability, affordability, and accessibility of reliable healthy eating information, is essential for fostering healthy eating intentions.

Keywords: digital health information; healthy eating; information-seeking ability; intention; e-health literacy

1. Introduction

Healthy eating constitutes the foundation of overall well-being, influencing mental, social, and physical health across humanity. Professionals' actions in promoting healthy eating behaviors play a pivotal role in fostering these positive outcomes. Research suggests that encouraging healthy eating behaviors is more effective than merely discouraging unhealthy ones (Adriaanse et al., 2011). A study involving 297 adults in Italy identified perceived benefits, a healthy lifestyle, knowledge about healthy foods, and eating satisfaction as direct predictors of behavioral intentions toward healthy eating (Savelli & Murmura, 2023). Eating with intention involves mindful planning and purposeful decision-making aimed at achieving better health. It emphasizes setting goals for balanced eating and making choices that support a healthy diet (Stowell, 2022).

Among multiple factors, seeking health information can positively contribute to healthy eating intentions. Nutbeam (2008) emphasizes that health information-seeking involves a combination of behavioral and cognitive dimensions, including skill-building, motivation, and a proactive approach to personal health. In this context, seeking healthy eating information promotes health by encouraging individuals to explore and integrate beneficial dietary behaviors actively.

Various sources of information contribute to improved knowledge of healthy eating (Savelli & Murmura, 2023). In today's digital age, access to health-related information has been transformed by the rise of online resources. Besides conventional health information sources (e.g., healthcare professionals, hospitals, books, government health agencies, friends and family, etc.), individuals increasingly turn to the Internet for dietary guidance, wellness tips, and nutritional advice. The skills required for effective online information-seeking become essential for promoting healthy eating behaviors. Research shows that individuals who obtain nutritional information online often improve their dietary quality, becoming more aware and confident in their food choices (Sassenberg & Greving, 2016).

However, the online environment also presents challenges, such as the spread of misinformation and disinformation. Social media platforms, in particular, frequently circulate conflicting dietary advice based on popular trends rather than evidence-based guidance (Beck et al., 2020). As technology increasingly shapes healthcare systems and personal health management, the World Health Organization (WHO) underscores digital health literacy as a fundamental skill (WHO, 2020). It emphasizes an individual's capacity to navigate and make use of digital tools to enhance personal health practices.

E-health literacy, defined as the ability to understand, find, and apply online health information, encompasses skills in accessing, evaluating, and utilizing information regarding health in a digital environment effectively (Norman & Skinner, 2006). In the context of healthy eating, e-health literacy is particularly vital, as research consistently links diet quality to lifestyle-related diseases such as obesity, cancer, diabetes, and cardiovascular conditions (Scully et al., 2017). Online health information resources range from government nutrition databases and health-related forums to popular social media platforms. However, these sources vary significantly in accessibility, reliability, and quality, necessitating strong analytical skills from users to critically assess the information they encounter (Diviani et al., 2015).

These challenges underscore the critical need to understand the effects of information-seeking skills and e-health literacy, as well as their interaction with individuals' probability of developing healthy eating intentions.

Several studies have been conducted to study factors influencing healthy eating intentions and behaviors within the Iranian population. Farahmand et al. (2012)

identified key barriers to healthy eating among Iranian women, including interpersonal and cultural influences, limited access to healthy foods, and entrenched food preferences. Farhangi, Dehghan, and Jahangiry (2018) revealed that Iranian female adolescents often engage in meal skipping and frequent snacking; these behaviors are linked to emotional disorders and unhealthy eating patterns. More recent studies emphasize the importance of educational interventions in addressing these challenges. Ashrafi et al. (2023) found that eating habits significantly influence healthy eating behaviors among Iranian adolescents, recommending targeted educational programs to promote healthier practices. Ebrahimi, Ghofranipour, and Tavousi (2017) demonstrated the effectiveness of educational interventions in improving healthy eating behaviors among Iranian school-aged students. Similarly, Shahroodi et al. (2021) highlighted the positive impact of such interventions on the nutritional behaviors of Iranian women, underscoring the critical role of education in fostering sustainable healthy eating habits.

Nevertheless, research exploring the effects of digital information-seeking skills, e-health literacy, and their interaction on healthy eating intention remains limited. Mostafazadeh et al. (2024) found that nutritional literacy accounted for 44% of the variance in eating behaviors among Iranian nursing students. Nutritional literacy, as defined by Malloy-Weir and Cooper (2016), reflects an individual's ability to obtain, process, and understand basic nutritional information and services to make informed eating decisions. While the finding of Mostafazadeh et al. (2024) underscores the critical role of information-seeking and information-processing in shaping healthy eating patterns within the Iranian population, it has not captured the effects of information-seeking and -processing capabilities as well as health literacy on the digital environment.

To fill in this gap, the current study aims to employ the Bayesian Mindsponge Framework (BMF) analytics on a dataset of 9775 Iranian adults to answer the following research questions:

- How are healthy eating information-seeking ability and e-health literacy associated with healthy eating intention?
- Is there any moderation effect of e-health literacy on the relationship between healthy eating information-seeking ability and healthy eating intention?

2. Method

2.1. Theoretical Foundation

The mindsponge theory (MT), initially introduced by Vuong and Napier (2015) as the mindsponge mechanism, provides the conceptual foundation for the two research questions outlined in the introduction (Vuong, 2023). MT has continuously shown its effective application in various fields, including health and positive psychology, to explore the psychological mechanisms underlying the relationship between the information-processing mechanism in the human mind and health considerations in food consumption (Sari, Mazenda, & Tristiana, 2025). In the field of food research, MT has been used to distinguish domestic from international students in how they perceive the difficulties of adjusting to new foods (Jin et al., 2023). This makes MT particularly suitable for explaining the dynamics between healthy eating information-seeking ability, e-health literacy, and healthy eating intention in the Iranian population.

Initially, the mindsponge mechanism was used to explain the dynamics of acculturation and global thinking (Vuong & Napier, 2015). Later, the mindsponge mechanism was developed to be a more comprehensive mindsponge theory by incorporating evidence from life and neurosciences, with the absorption-ejection information-processing of the mindsponge mechanism being a pivotal component (Vuong, 2023). More recently, MT has been upgraded into a granular interaction thinking theory, with the granular interaction mechanism now being central (Vuong & Nguyen, 2024a, 2024b). By integrating principles from quantum physics (Rovelli, 2016, 2018; Keppens, 2018) and Shannon's information theory (Shannon, 1948), the upgraded MT introduces an entropy-based notion of value to explain better the complexity of human psychology and behavior phenomena shaped by various mental processes (Vuong & Nguyen, 2024a, 2024b; Davies & Gregersen, 2014; Nguyen, 2024).

According to MT, the healthy eating intention can be viewed as an outcome of mental information processing, which is driven by the information absorption, evaluation, and filtering processes. Specifically, when individuals possess a greater capability to seek healthy eating information (either from healthcare professionals, hospitals, books, government health agencies, friends and family, etc.), they can have a higher probability to access and absorb healthy eating information, which can subsequently contribute to the emergence of healthy eating intention within the mind. Normally, the absorbed information has the chance to be filtered out if it does not resonate with the individuals' mindset (or the set of core values). In this study's context, it should be noted that health information-seeking action already involves the motivation and proactiveness to improve personal health (Nutbeam, 2008), so people more capable of seeking healthy eating information are also more likely to possess the motivation of healthy eating already. Thus, we can exclude the scenario that absorbed healthy eating information will be filtered out due to the mismatch with the individuals' core values. Instead, we expect the capability of seeking healthy eating information to reinforce the absorption of that information further and, subsequently, the emergence of healthy eating intention by making it more feasible and/or even more beneficial (i.e., reducing the perceived costs and improving the perceived values of healthy eating for better health status and improved quality of life).

In the digital age, the Internet has become an important source of health information. However, for effectively seeking and absorbing healthy eating information on the Internet, e-literacy is critical. Research has found that higher health literacy and greater access to technological devices like smartphones, computers, or tablets are linked to more frequent health-related information-seeking online (Lee et al., 2021). Individuals with higher levels of e-health literacy are better equipped and more confident in distinguishing accurate health information from biased or misleading content (Kim & Xie, 2017). Moreover, those who actively seek nutrition-related information online are significantly more likely to adopt health-promoting dietary behaviors, as they possess the capacity to process and implement evidence-based practices effectively (Dutta-Bergman, 2004).

MT suggests that the process of absorbing, evaluating, and filtering online information about healthy eating depends on individuals' e-health literacy, which encompasses a range of technical skills, cognitive abilities, and social competencies that enable individuals to effectively navigate, interpret, and utilize health information (Norman & Skinner, 2006). When individuals possess adequate e-health literacy, they will be more likely to seek, evaluate, and utilize information about healthy foods and eating styles from online sources, further facilitating the emergence of healthy eating intentions within their minds. More specifically, for those seeking to improve dietary practices, a higher level of e-health literacy can be positively associated with better decision-making, as it equips individuals to interpret and apply dietary recommendations tailored to their specific needs (Dunn et al., 2014). Furthermore, e-health literacy fosters autonomy in dietary choices, enabling individuals to rely on evidence-based nutrition guidance rather than generalized or unverified advice (Mackert et al., 2016).

Conversely, when individuals lack the ability to find valid and reliable information online due to insufficient e-health literacy, they are more likely to encounter low-quality or misleading details or less likely to utilize online healthy eating information sources. In other words, we expect e-health literacy will not only be positively associated with healthy eating intention but also positively moderate the relationship between healthy eating information-seeking ability and healthy eating intention, especially among the adult population.

2.2. Model construction

2.2.1. Variable selection and rationale

This study used primary data from a dataset of 9755 people living in Qazvin province, Iran (Pakpour et al., 2023). The dataset was peer-reviewed and published in *Data in Brief* with the aims of increasing transparency, having the dataset validated by other experts, facilitating the reproduction of analysis results, and offering resources for other researchers to create additional knowledge in the study field (Vuong, 2017, 2018, 2020). The dataset contains socio-demographic information and measurements of health literacy, e-health literacy, mental well-being, and sleep hygiene behaviors, which were collected between January and April 2022 (Pakpour et al., 2023). The detailed information regarding this dataset is accessible online by address:

https://www.sciencedirect.com/science/article/pii/S2352340923001907

In the current study, we extracted three variables from the dataset to be employed in statistical analysis (see Table 1). To measure the healthy eating information-seeking ability from online and offline sources, we employed variables of *AbilityFindingHealthyEatingInfo,* which was generated from variable *Atl2* in the original dataset). For e-health literacy, *eHealthLiteracy* (average value of eight items in eHealth Literacy Scale or eHEALS) was generated, which reflected the degree of individual ability in seeking, processing, and utilizing the health information and services available online. To measure the degree of healthy eating intention among the Iranian population, we employed the variable *HealthyEating*, which was generated from four items *DM5*, *DM9*, *DM10*, and *DM12* in the original dataset (Cronbach's Alpha = 0.847). Table 1 below explains the variables' description in detail.

Table 1. Variable description

Variable's Name	Description	Data Type	Value
HealthyEating	The individual's intention to perform healthy eating behavior.	Numerical	1=Never 2=Rarely 3=Sometimes 4=Usually 5=Always
AbilityFindingHealthyEatingInfo	The degree of individual ability to seek information regarding healthy eating.	Numerical	
eHealthLiteracy	The degree of individual capacity to obtain, process, and understand basic health information and services available online for appropriate health decisions.	Numerical	

2.2.2. Statistical model

To tackle this study aim, we formulated Model 1 with the following structure:

$$HealthyEating \sim \text{normal}(\mu, \sigma) \quad (1.1)$$

$$\mu_i = \beta_0 + \beta_1 * AbilityFindingHealthyEatingInfo_i + \beta_2 * eHealthLiteracy_i + \beta_3 * AbilityFindingHealthyEatingInfo * eHealthLiteracy_i \quad (1.2)$$

$$\beta \sim \text{normal}(M, S) \quad (1.3)$$

The probability around μ is determined by the form of normal distribution, whose width is specified by the standard deviation σ. The healthy eating intention of Iranian i is indicated by μ_i. The model has an intercept β_0 and three coefficients, β_1-β_3. The coefficients of the predictor variables are distributed as a normal distribution around the mean denoted M and with the standard deviation denoted S. The logical network of Model 1 is shown in Figure 1.

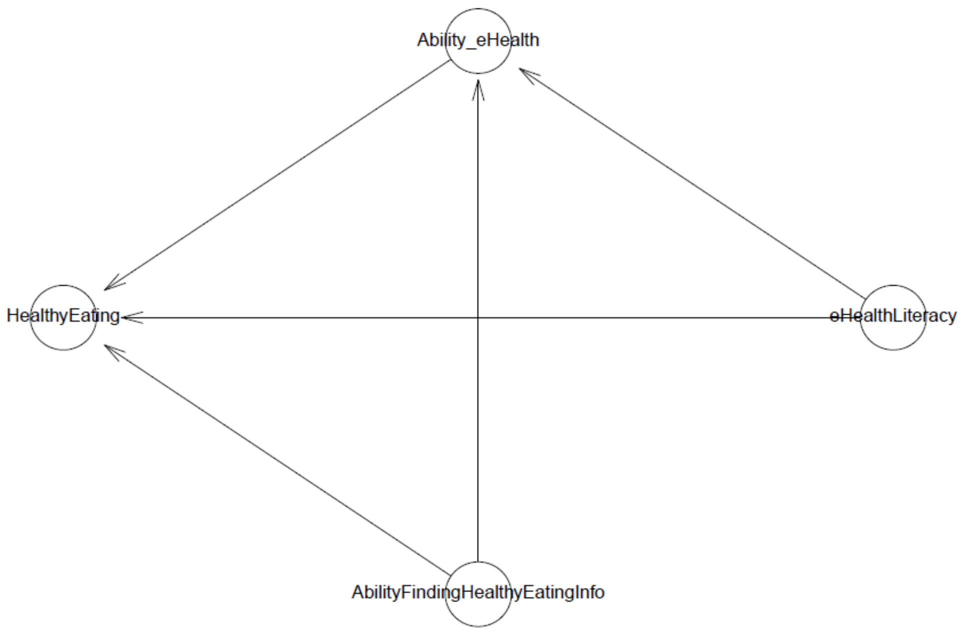

Figure 1. Logical network of Model 1

2.3. Analysis and validation

This study utilized the Bayesian Mindsponge Framework (BMF) analytics for several key reasons (Nguyen et al., 2022; Vuong, Nguyen, & La, 2022). The BMF approach combines the logical reasoning of Mindsponge Theory with the inferential strengths of Bayesian analysis, making it an effective analytical framework for our study.

Bayesian inference treats all parameters probabilistically, enabling the reliable prediction of parsimonious models (Csilléry et al., 2010; Gill, 2015). This offers several advantages over traditional frequentist approaches, such as the use of credible intervals for result interpretation instead of relying solely on *p*-values (Halsey et al., 2015; Wagenmakers et al., 2018). Additionally, Bayesian analysis with informative priors can address multicollinearity problems and weak data issues (Adedayo & Ojo, 2018; Jaya et al., 2019; Leamer, 1973).

Choosing appropriate priors is crucial during model building (van de Schoot et al., 2021). As our study is exploratory, we initially employed uninformative priors to minimize subjectivity. We then conducted a sensitivity analysis using a prior-tweaking method by re-running the analysis with informative priors designed to reflect a neutral belief in associations. These informative priors were specified using a normal distribution with a mean of 0 and a standard deviation of 0.5. If the estimated outcomes were consistent across both sets of priors, the results were deemed robust. Following the model fitting process, we employed Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics to assess the goodness-of-fit of the model (Vehtari & Gabry, 2019; Vehtari et al., 2017). The LOO computation procedure is outlined as follows:

$$LOO = -2LPPD_{loo} = -2\sum_{i=1}^{n} \log \int p(y_i|\theta) p_{post(-i)}(\theta) d\theta$$

The posterior distribution $p_{post(-i)}(\theta)$ denotes the posterior distribution computed after excluding observation i. In the PSIS method, k-Pareto values are used to identify influential observations. Values below 0.5 indicate that the model fits well, while values above 0.7 suggest the presence of influential data points affecting the LOO estimate.

For models demonstrating a good fit, we proceeded with convergence diagnostics and result interpretation. We used both statistical measures and visual illustrations to validate convergence. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) were employed. The *n_eff* value larger than 1000 indicates a sufficient number of effective samples for reliable inference (McElreath, 2018). The *Rhat* value should be close to 1 for convergence, with values exceeding 1.1 indicating non-convergence (Brooks & Gelman, 1998). Visually, convergence was assessed using trace plots of the Markov chains.

The Bayesian analysis was conducted in R using the open-access **bayesvl** package, which offers robust visualization capabilities (La & Vuong, 2019). To ensure data transparency and facilitate reproducibility, all data and code snippets from this study have been deposited on a preprint server for public access and reuse (Vuong, 2018). The dataset and code can be accessed at: https://zenodo.org/records/13859254

3. Results

Before interpreting the results of BMF analytics, it is necessary to evaluate how well Model 1a fits the data. As can be seen in Figure 2, we found no value exceeding the 0.1 threshold; the recommended value is below the 0.7 threshold. This indicates a good fit signal between the model and the data.

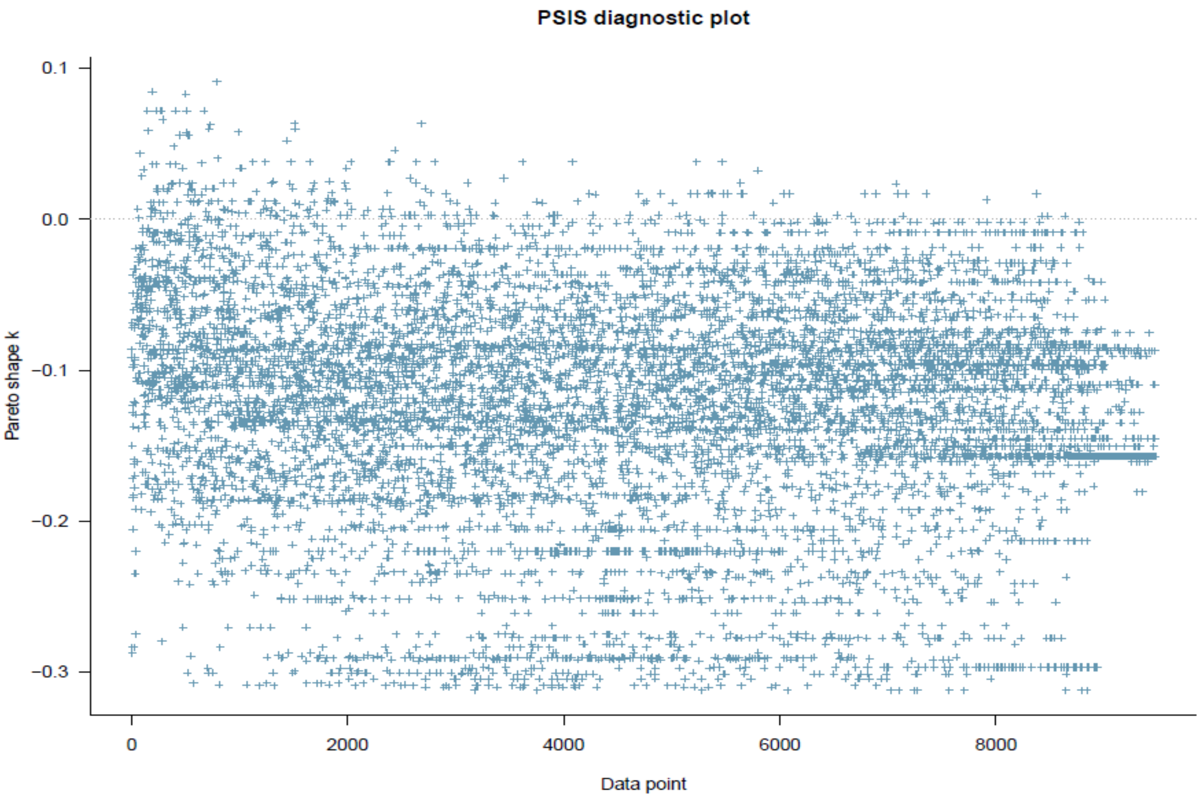

Figure 2. Model 1's PSIS-LOO diagnosis

The posterior distribution statistics of Model 1a are shown in Table 2. All *n_eff* values are higher than 1000, and all *Rhat* values are equal to 1, which indicates a good convergence of the simulation results. Trace plots in Figure 3 also confirm the convergence of the simulated iterations around the central equilibrium, so the estimated results are eligible for interpretation. Table 2 below explains the posterior distribution statistics of Model 1a, as illustrated in Figure 1.

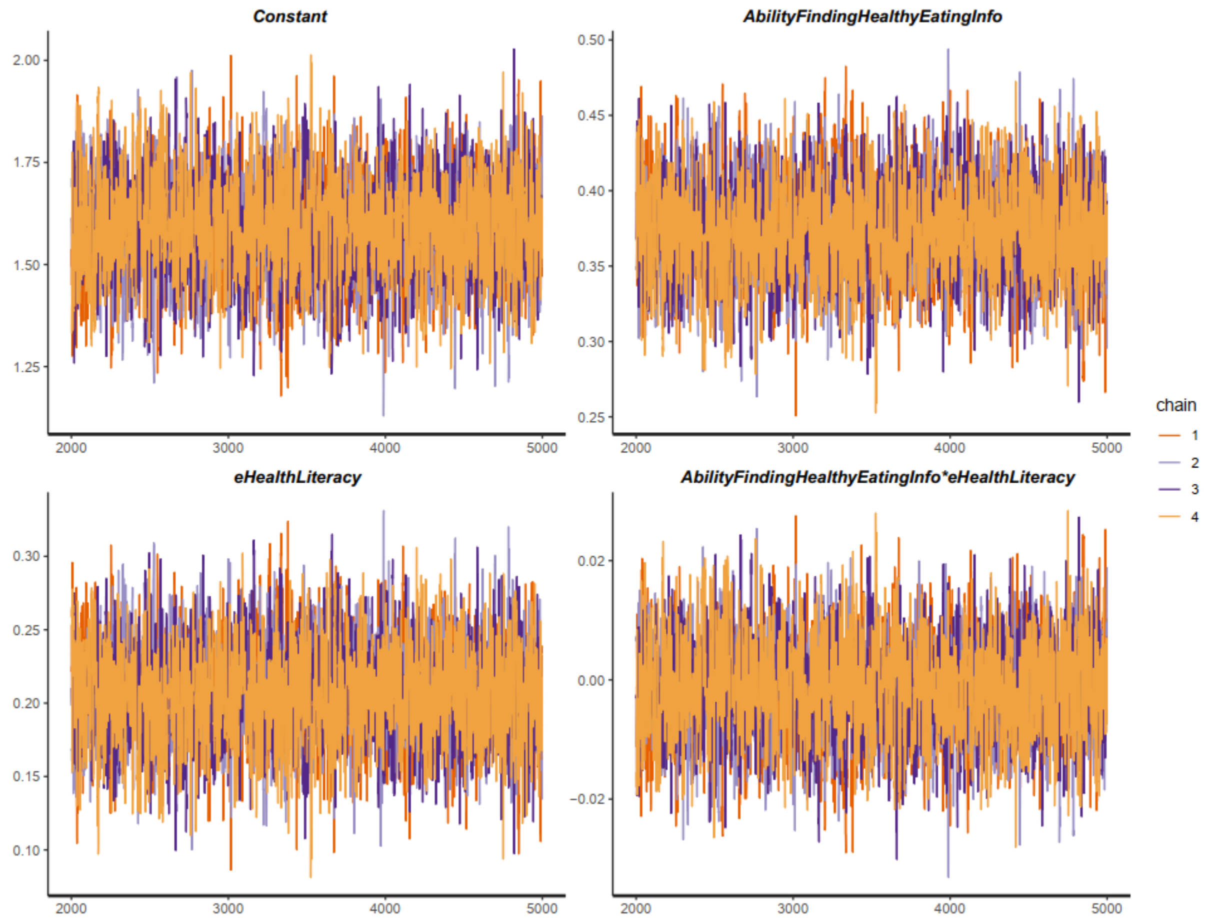

Figure 3. Model 1's trace plots

Table 2. Estimated results of Model 1

Parameters	Uninformative priors				Informative priors			
	Mean	**SD**	**n_eff**	**Rhat**	**Mean**	**SD**	**n_eff**	**Rhat**
Constant	1.59	0.12	2324	1	1.60	0.11	2454	1
AbilityFindingHealthyEatingInfo	0.37	0.03	2357	1	0.37	0.03	2362	1
eHealthLiteracy	0.21	0.03	2434	1	0.20	0.03	2242	1
AbilityFindingHealthyEatingInfo eHealthLiteracy*	0.00	0.01	2341	1	0.00	0.01	2354	1

Figure 4 illustrates the estimated posterior distributions of Model 1. As can be seen, the distributions of *AbilityFindingHealthyEatingInfo* and *eHealthLiteracy* are located entirely on the positive side of the *x*-axis, while the distribution of *AbilityFindingHealthyEatingInfo* eHealthLiteracy* is situated around 0. The illustration implies the highly reliable positive associations between *AbilityFindingHealthyEatingInfo* and *eHealthLiteracy*, and *HealthyEating*, as well as the ambiguous relationship between *AbilityFindingHealthyEatingInfo* eHealthLiteracy* and *HealthyEating*. The estimated results using informative priors are almost identical to those using uninformative priors, so the estimated results are insensitive against priors.

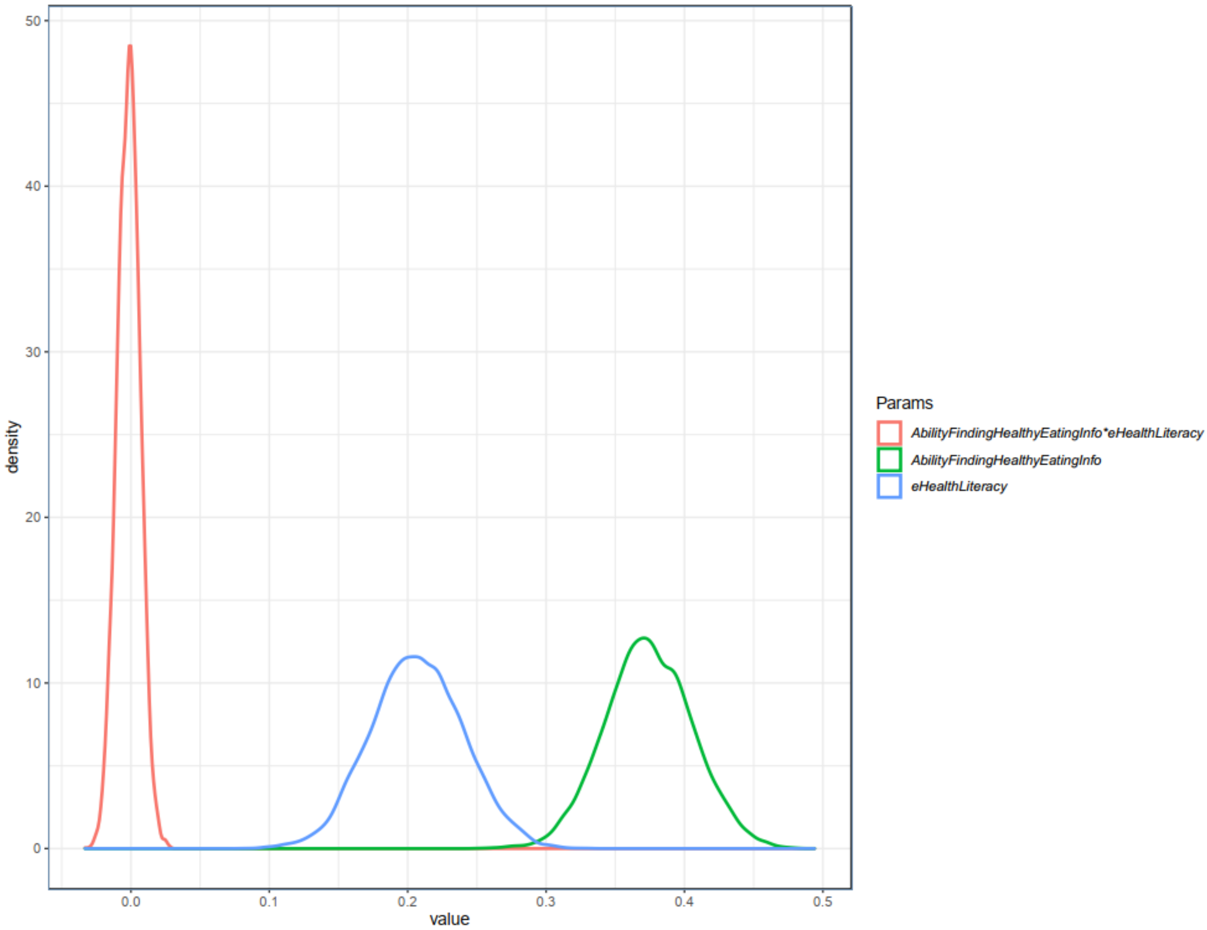

Figure 4. The estimated posterior distributions of Model 1's coefficients

4. Discussion

The BMF analytics was used to examine how healthy eating information-seeking ability and e-health literacy are associated with healthy eating intention among adults living in Iran.

This study's findings showed that healthy eating information-seeking ability is positively associated with healthy eating intention among Iranian adults. The more capable ones seek healthy eating information, either from online or offline sources, resulting in a higher healthy eating intention. Lee et al. (2022) indicated that the behavior and attitude of an individual may influence health through related information-seeking of food. Results were corroborated by the studies by Kilb et al. (2023) and McKinley & Wright (2014), who reported that healthy eating intentions can result from obtaining health information online, which is impacted by informational social support. A study in China indicates that nutrition information from various sources is worth promoting because consumers who were more involved in nutrition information tended to eat healthier (Wang, Wang, & Shen, 2022). Both online and offline sources of healthy eating information play a vital role in supporting individuals through the various stages of consciously transitioning to a healthier diet. Bridging the interconnection between these sources is essential for fostering a sustainable, healthy eating lifestyle (Feher et al., 2021).

This study's findings also showed that e-health literacy is positively associated with healthy eating intention among Iranian adults. To elaborate, the more capable one is of finding, understanding, evaluating, and applying online health information, the more one will have higher healthy eating intentions. Lee et al. (2022) indicated that the behavior and attitude of an individual may influence health through related e-health literacy of food. Similarly, studies by Yang et al. (2017) and Kim and Oh (2021) highlighted a correlation between e-health literacy—particularly the critical skill of evaluating online information—and improved health-promoting behaviors, including healthy eating. In alignment, Fehér et al. (2021) noted that e-health literacy competencies of university students, like accessing, evaluating, and utilizing online health information, support their transition to a healthier diet. Kim et al. (2019) further found that office workers' intentions to engage in health-related behaviors, including seeking online health information, are strongly influenced by their e-health literacy and perceived value of the information. Therefore, promoting healthy eating across diverse demographics can be achieved by improving e-health literacy, enhancing online information-seeking skills, and ensuring the availability of reliable online health information to the broader public (Fitzpatrick, 2023).

Nevertheless, we found an ambiguous moderation effect of e-health literacy on the relationship between healthy eating information-seeking ability and healthy eating intention. This finding indicates that increased e-health literacy has not contributed significantly to the connection between healthy eating information-seeking and intention to eat healthily. The ambiguous moderation effect, together with the positive effects of healthy eating information-seeking ability and e-health literacy on healthy eating intention, suggests that there might exist two different groups that have clearly different healthy eating information-seeking strategies: 1) one seeking information through offline sources (e.g., healthcare professionals, hospital staffs, books and other printed media, government health agencies, friends and family) and 2) one seeking information through online sources. The members of the group seeking information from offline sources seem not to use online sources as e-health literacy has an ambiguous moderation effect on their information-seeking capability and healthy eating intention.

This explanation is supported by Ramachandran et al. (2023), who postulated that even with the increase in technological usage, individuals who are exposed to and prefer traditional methods of acquiring information may not benefit from e-health information and literacy (Ramachandran et al.,2023). This is also corroborated by studies from Elgamal (2024) and Britt & Hatten (2013), who reported that the link between e-health literacy and information seeking was not shown to be moderated by the need for cognition. However, further studies are still required to examine whether these two distinct groups exist. If yes, what are their characteristics? And what information communication strategies should be used to enhance their healthy eating intentions effectively?

In general, online access to healthy eating information plays a crucial role in promoting the adoption of healthy meals at the individual level. In the digital age, individuals increasingly prioritize and make concerted efforts to seek out online resources on health and nutrition. This underscores the importance of the availability, affordability, and accessibility of such information, which can significantly influence healthy eating habits. Online information has become the preferred source for most individuals today, making e-health literacy a critical skill for achieving better health outcomes. However, there might be a group of people who still prefer seeking information from offline sources, so the roles of offline sources should not be underestimated. Improving the availability, affordability, and accessibility of healthy eating information through those sources is, therefore, necessary.

This study was not without limitations. The study used a cross-sectional design, so the causal inference from the study's findings should be cautious. Moreover, the data in this study were collected in one province of Iran, which possibly hinders its representativeness and generalizability. Although digitalization has been evolving, there was the possibility of participants not having continual access to the Internet, hampering universal access to e-health information and literacy. Furthermore, the quality of the information received by participants in the current study was not measured. As more and more aspects of society, including health care, are moving online, there is a challenge of individuals being able to distinguish between reliable and inaccurate information and to promote the use of high-quality online health information that will aid in improving health literacy and, ultimately, healthy meals.

5. Recommendations

Improving health information literacy is crucial, particularly for individuals who are illiterate, less knowledgeable, or from low-income backgrounds. Addressing these challenges requires the development and implementation of food literacy pathways to health. This involves creating education and training programs that equip individuals with the knowledge, skills, and resources needed to access, prepare, and cook nutritious foods. Such programs should ensure accessibility and relevance for all communities, especially those most vulnerable to food illiteracy and malnutrition. By targeting at-risk populations, these initiatives can promote equitable opportunities for adopting healthier dietary practices.

Laws ensuring equitable access to healthy food and accurate nutritional information, particularly for underserved populations, should be prioritized. Efforts should also focus on expanding access to technology and providing alternative methods for households without digital access to communicate and receive health information. In rural areas lacking broadband internet, this could involve enhancing cellular connectivity and broadband infrastructure while ensuring public facilities, such as libraries, are equipped with sufficient computers for online access. Privacy safeguards must be implemented to protect individuals' private health information during such activities. By leveraging these opportunities and fostering partnerships, we can pave the way for a future where nutrition and food literacy become powerful tools to improve public health, reduce disparities, and cultivate a culture of informed healthy living.

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