Understanding the Supportive Care Needs of Family Caregivers in Cancer Stress Management: The Significance of Healthcare Information

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Abstract

Cancer care has transitioned from clinical-based to home-based care to support long-term care in a more familiar and comfortable environment. This care transition has put family caregivers (FCGs) in a strategic position as care providers. Cancer care at home involves psychological and emotional treatment at some point, making FCGs deal with the stress of cancer patients frequently. Due to their limited care competencies, they need supportive care from healthcare professionals in cancer stress management. This study aims to examine how types of demanded healthcare information affect the FCG's role in reducing the stress of female cancer patients. The mindsponge theory was used in conceptual development and interpretation. Bayesian Mindsponge Framework (BMF) analytics were used for statistical analysis on a dataset of 48 spouses (husbands) and 12 other family members in five congested communities of Surabaya, Indonesia. Results showed that among the six types of healthcare information, FCGs with higher demand for cancer-specific information were more likely to need support in reducing the stress of female cancer patients. Meanwhile, FCGs with a higher demand for information about support services were less likely to need support to reduce cancer patients' stress. Other types of healthcare information have ambiguous effects on the need for support in reducing cancer-induced stress. This study reveals that the demanded cancer-specific information, e.g., cancer prognosis or likely outcome, must be prioritized to assist FCG's role in managing cancer stress.

Keywords: cancer; stress; family caregiver; healthcare information; mindsponge theory; Bayesian Mindsponge Framework.

> "[…] under good care and continuing using the panacea, Kingfisher's appetite for fish had returned. The birds brought tasty fat carp, and so he recovered quickly."
> —In: "Kingfisher's No-Fish Dietary"; *The Kingfisher Story Collection* (Vuong, 2022)

1. Introduction

Cancer, a pervasive threat cutting across geographical boundaries, significantly strengthens its control, especially in low-income and middle-income countries (Shah et al., 2019). Among the numerous challenges posed by cancer, breast and cervical cancers emerge as the foremost afflictions affecting women in these areas (Denny et al., 2017). According to the World Health Organization (WHO), cervical cancer ranks as the fourth most prevalent cancer worldwide, recording 604,000 new cases and 342,000 deaths in 2020, underscoring its substantial implications for women's well-being (Choi et al., 2023). This is particularly conspicuous in Indonesia, where these cancers have alarmingly secured the unsettling position of being the leading causes of death (Kristina et al., 2022; Solikhah et al., 2020). In 2013, the cancer prevalence in Indonesia was 1.4%, with rates of 0.8‰ for breast cancer and 0.5‰ for cervical cancer. By 2017, breast cancer ranked highest for both new cases and deaths, with cervical cancer in the second position (Sari, 2020).

In response to the changing healthcare landscape, there is a substantial shift towards delivering care to individuals in the terminal stages of illnesses, including cancer patients, within the comfort of their homes (Nysæter et al., 2022; Tralongo et al., 2011). This transition places the primary responsibility on family caregivers (FCGs), who face the formidable task of providing daily care to their unwell family members (Sun et al., 2023). However, this shift is not without challenges, as it is described as burdensome and overwhelming due to frequently unmet needs, casting a shadow over the caregiving experience (Mitchell et al., 2018).

Numerous studies consistently underscore the essential support needed by family caregivers engaged in cancer patient care, especially concerning breast and cervical cancers (Kusi et al., 2020; Bechthold et al., 2023). The literature emphasizes the pivotal role of caregivers in addressing patients' challenges during treatment, emphasizing that fulfilling caregivers' needs significantly shapes the overall caregiving experience (Kwame and Petrucka, 2021; Molassiotis and Wang, 2022; Otis-Green and Juarez, 2012). Previous research identifies specific caregiver requirements for patient health and physical care information, covering emotional and relational needs, practical needs, work, and social needs, as well as healthcare and illness-related needs (Kwame and Petrucka, 2021; Molina-Mula and Gallo-Estrada, 2020; Reinhard et al., 2008; Wackerbarth and Johnson, 2002; Zamanzadeh et al., 2015).

Simultaneously, these studies highlight the widespread lack of healthcare information fulfillment among family caregivers, particularly in critical areas like illness and treatment information, which is crucial for effective caregiving (Teixeira et al., 2020; Wackerbarth and Johnson, 2002). Furthermore, caregivers expressing significant interest in guidelines and information related to complementary and alternative medicine encountered unresponsiveness in meeting these specific needs (Plachkinova et al., 2019; Xie et al., 2018).

Existing literature acknowledges the challenges faced by family caregivers of female cancer patients and recognizes the importance of addressing their supportive care needs. However, there is a noticeable gap in understanding the relationship between demanded healthcare information and the role of family caregivers in reducing the stress of cancer patients, particularly in the context of breast and cervical cancers. Limited insight exists into how specific types of information needs may either alleviate or contribute to the stress experienced by female cancer patients.

Understanding the impact of different types of demanded healthcare information on the role of FCGs in reducing the stress of female cancer patients is crucial. In this study, we examined various types of healthcare information that caregivers require, encompassing insights into breast and cervical cancers, treatment details, and support services guidance. This study aims to examine how types of demanded healthcare information affect the FCG's role in reducing the stress of female cancer patients (i.e., cancer-specific information, caregiver-specific information, therapy-specific information, information on cancer physical needs, information on alternative therapies, and information on support services). Through this examination, we aimed to understand how providing the right information can assist caregivers in reducing cancer-induced stress in their crucial role, contributing valuable insights to enhance the support system for caregivers and patients, ultimately improving the overall quality of cancer care.

2. Method

2.1. Theoretical Foundation

Mindsponge theory (MT) was used in conceptual development and result interpretation (Vuong, 2023). MT views the human mind as an information processor that filters, processes, and accepts or rejects new information or values into or out of the mindset or core values. MT considers the human mind's filtering system the key factor of the whole information-processing mechanism (Mantello et al., 2023). In filtering new information or values, subjective cost-benefit judgments play an important role, and these may be influenced and be meaningful only if considering the sociocultural context of the individuals (Vaughn, 2019). The new information may become a new mindset or ejected from the human mind depending on the results of these subjective judgments. MT uses the human mind's information-processing approach to explain various mental products, e.g., stress, and complex human behavior, such as adaptation.

This study regards the FCG's mind and social environment in a community setting as the main spectrums. MT views the caregiving mindset as a set of cancer care-related core values in the human mind. New healthcare information related to cancer caregiving will be absorbed to become a new mindset or accepted if the results of subjective cost-benefit judgments are positive. As the information filtering process can be energy- and time-consuming, the human mind may employ trust in information sources as the gatekeeper of prioritized information channels to catalyze new information reception and interpretation (Le, Nguyen, & Vuong, 2022). The new trusted information may be used as a reference in subsequent information-filtering processes toward other new healthcare information available in a social environment.

Individuals may become an information source for one another. The unique human interaction involving two ways of communication results in back-and-forth influences in a social relationship context. Trust is the key to enhancing effective communication with stakeholders (Tanemura et al., 2022). At least four stakeholders are directly involved in cancer management in community settings: the patients, families (FCGs in this case), palliative volunteers, and healthcare professionals (Sari, 2020). Trust among stakeholders must be ensured, especially in risk communication, such that the message from public agencies, e.g., the Public Health Centre (PHC), is accepted by the public (Kinoshita, 2016). FCG is inherently responsible for risk management in cancer, including the adverse events that arise from cancer-induced stress, e.g., symptoms worsening. FCGs can protect themselves by avoiding unexpected events during cancer caregiving using preventive measures leveraging healthcare information. Therefore, sufficient information will be beneficial for effective decision-making in life-crisis situations.

Nursing repeatedly ranks as the most trusted profession in the healthcare field (Emler & Bornstein, 2023). The healthcare information provided by community nurses working in the PHC has a high possibility of being trusted by FCG, increasing the possibility of being accepted in FCG's mind to become a new caregiving mindset. If community nurses adequately assess the unmet needs of demanded healthcare information in FCG of cancer patients, it will be beneficial for assisting FCG's role in cancer stress management. In this study, FCG's role in cancer stress management may be assisted by meeting their needs on demanded healthcare information.

2.2. Study Design and Samples

This was a cross-sectional study. Five communities in Surabaya, Indonesia, were involved as study sites among 63 communities under the health management of a respectable PHC across the city. Firstly, cluster random sampling was implemented to select the five communities. Secondly, simple random sampling was implemented to select the respondents. 60 FCGs of female cancer patients, consisting of 48 spouses (husbands) and 12 other family members, participated in this study. There were no specific sample criteria required in this study. As long as the in-site PHC confirmed the cancer diagnosis of care recipients and the cancer patients confirmed that the prospective respondents were the primary FCG at home, these individuals were eligible to be study respondents.

2.3. Data Collection Procedure

All respondents were well-informed about this study's purposes, benefit-risk potencies, data collection procedure, and incentives prior to study participation. Exclusion criteria were rejection on filling out the consent form. This study protocol was reviewed by the Ethical Committee of the Faculty of Medicine, Widya Mandala Surabaya Catholic University, Indonesia, with an ethical clearance registered certificate of 082/WM12/KEPK/DOSEN/T/2020. Data were collected in February-March 2020. Enumerators collected the data by door-to-door approach. Respondents were asked to read and answer the question/statement in the instrument themselves, but assistance was provided for those in need. No conflict of interest between the authors and study funder was declared regarding this study and publication.

2.4. Study Instrument

The demography questionnaire was used to collect data on demography characteristics. It consisted of seven items identifying personal information of age, gender, marital status, education level, occupation, Gross Domestic Product (GDP) in Indonesian Rupiah (IDR), and housemate. The instrument SCNS-P&C45 (Supportive Care Needs Survey – Partners and Caregivers 45) was used to collect the data on FCG's supportive care needs. This is a specific instrument for assessing the unmet needs of partners and caregivers of people diagnosed with cancer (Centre for Health Research & Psycho-Oncology / CHeRP, The Cancer Council New South Wales, 2009). It could comprehensively assess the range of caregivers' supportive needs across the cancer trajectory. Researchers and clinicians can use it to determine caregivers' unmet needs, prioritize healthcare resources, and tailor supportive cancer care services accordingly.
SCNS-P&C45 comprises four domains in 45 items. Factor analysis revealed four domains of supportive care needs, such as 1) health care and illness-related needs (11 items), 2) emotional and relational needs (16 items), 3) work and social needs (11 items), and 4) practical needs (7 items). For each item of SCNS-P&C45, respondents were asked to indicate their level of supportive care needs over the last month as a result of caring for people with cancer by using the following response options:

1. No need: consists of "not applicable" (score 1) and "satisfied" (score 2).
2. Some need: consist of "low need" (score 3), "moderate need" (score 4), and "high need" (score 5).

Based on the Likert scale above, the unmet needs of FCG were divided into four categories, such as: no need (total score: 45-90), low need (total score: 91-135), moderate need (total score: 136-180), and high need (total score: 181-225). Based on the results of instrument testing on 30 FCG of female cancer patients in different communities, SCNS-P&C45 was proved to be a valid and reliable instrument for this study ($r = 0.277–0.761$; Chronbach Alpha = 0.965).

2.5. Model Construction and Analysis

2.5.1. Variable selection and rationale

Among all aspects, the unmet needs of healthcare information from the domain of healthcare and illness-related needs may affect FCG's role in reducing stress in female cancer patients from the domain of emotional and relational needs. In the current study, seven variables were employed for statistical analysis, namely: *StressReduction, Information_Caregiver, Information_Cancer, Information_SupportServices, Information_AlternativeThe, Information_PhysicalNeed,* and *Information_SideEffects.* To measure the FCG's needs in reducing the stress of female cancer patients, we employed the *StressReduction* variable, which reflects the FCG's unmet needs of emotional and relational needs in reducing stress in the person with cancer's life. The six types of demanded healthcare information that may affect the FCG's role in reducing the stress of female cancer patients (i.e., cancer-specific information, caregiver-specific information, therapy-specific information, information on cancer physical needs, information on alternative therapies, and information on support services) were represented by variables of *Information_Caregiver, Information_Cancer, Information_SupportServices, Information_AlternativeThe, Information_PhysicalNeed,* and *Information_SideEffects.*

Table 1. Variable Description

Variable's Name	Description	Data Type	Value
StressReduction	The need for reducing stress in the person with cancer's life	Numerical	1 = not applicable 2 = satisfied 3 = low need 4 = moderate need 5 = high need
Information_Caregiver	The need for accessing information relevant to your needs as a carer/partner	Numerical	
Information_Cancer	The need for accessing information about the person with cancer's prognosis or likely outcome	Numerical	
Information_SupportServices	The need for accessing information about support services for carers/partners of people with cancer	Numerical	
Information_AlternativeThe	The need for accessing information about alternative therapies	Numerical	
Information_PhysicalNeed	The need for accessing information on what the person with cancer's physical needs are likely to be	Numerical	
Information_SideEffects	The need for accessing information about the benefits and side effects of treatments	Numerical	

2.5.2. Statistical Model

In this study, we positioned the types of demanded healthcare information as predictors of the FCG's needs in reducing the stress of female cancer patients. We constructed the analytical model based on the theoretical foundation of MT as presented below:

$$StressReduction \sim normal(\mu, \sigma) \tag{1}$$

$$\mu_i = \beta_0 + \beta_{Information\_Caregiver\_StressReduction} * Information\_Caregiver_i + \beta_{Information\_Cancer\_StressReduction} * Information\_Cancer_i + \beta_{Information\_SupportServices\_StressReduction} * Information\_SupportServices_i + \beta_{Information\_AlternativeThe\_StressReduction} * Information\_AlternativeThe_i + \beta_{Information\_PhysicalNeed\_StressReduction} * Information\_PhysicalNeed_i + \beta_{Information\_SideEffects\_StressReduction} * Information\_SideEffects_i \tag{2}$$

$$\beta \sim normal(M, S) \tag{3}$$

The probability around μ is determined by the form of normal distribution, with the standard deviation σ. The degree of unmet needs in reducing the stress of female cancer patients of FCG i is indicated by μ_i. $Information\_Caregiver_i$, $Information\_Cancer_i$, $Information\_SupportServices_i$, $Information\_AlternativeThe_i$, $Information\_PhysicalNeed_i$, and $Information\_SideEffects_i$ are the types of demanded healthcare information of FCG i. The model has an intercept β_0 and six coefficients of $\beta_{Information\_Caregiver\_StressReduction}$, $\beta_{Information\_Cancer\_StressReduction}$, $\beta_{Information\_SupportServices\_StressReduction}$, $\beta_{Information\_AlternativeThe\_StressReduction}$, $\beta_{Information\_PhysicalNeed\_StressReduction}$, and $\beta_{Information\_SideEffects\_StressReduction}$. The probability around β is also in the form of a normal distribution.

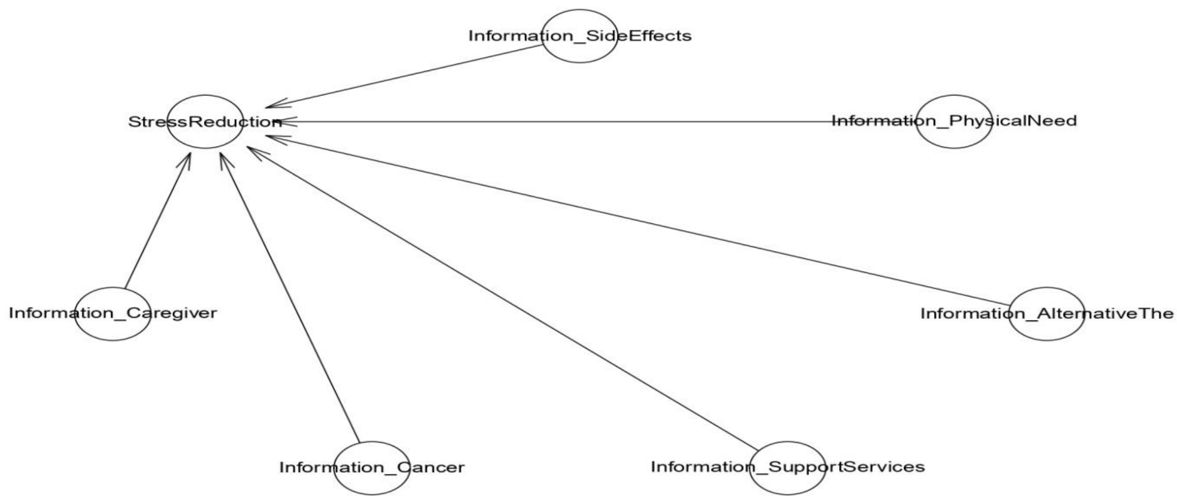

Figure 1. Model 1's logical network

2.5.3. Analysis and Validation

Bayesian Mindsponge Framework (BMF) analytics was employed in the current study for several reasons (Nguyen et al., 2022; Vuong, Nguyen, & La., 2022). First, the analytical method integrates the logical reasoning capabilities of MT with the inferential advantages of Bayesian analysis, exhibiting a high degree of compatibility (Nguyen et al., 2022). Second, Bayesian inference is a statistical approach that treats all the properties (including the known and unknown ones) probabilistically (Csilléry et al., 2010; Gill, 2015), enabling reliable prediction of parsimonious models. Nevertheless, utilizing the Markov chain Monte Carlo (MCMC) technique still allows Bayesian analysis to deal effectively with various intricate models, such as multilevel and nonlinear regression frameworks (Dunson, 2001). Third, Bayesian inference has various advantages in comparison to the frequentist approach. One notable advantage is the ability to utilize credible intervals for result interpretation instead of relying solely on the dichotomous decision based on *p*-values (Halsey et al., 2015; Wagenmakers et al., 2018). The Bayesian analysis was performed on R using the **bayesvl** open-access package, which provides good visualization capabilities (La & Vuong, 2019).

In Bayesian analysis, selecting the appropriate prior is required during the model construction process. Due to the exploratory nature of this study, uninformative priors or a flat prior distribution were used to provide as little prior information as possible for model estimation (Diaconis & Ylvisaker, 1985). The Pareto-smoothed importance sampling leave-one-out (PSIS-LOO) diagnostics was employed to check the models' goodness of fit (Vehtari & Gabry, 2019; Vehtari, Gelman, & Gabry, 2017). LOO is computed as follows:

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

$p_{post(-i)}(\theta)$ is the posterior distribution calculated through the data minus data point i. The k-Pareto values are used in the PSIS method for computing the LOO cross-validation in the R **loo** package. Observations with k-Pareto values which greater than 0.7 often considered influential and problematic for accurately estimating LOO cross-validation. When a model's k values are less than 0.5, it is typically regarded as being fit.

If the model fits well with the data, we will proceed with the convergence diagnoses and result interpretation. In the current study, we validated the convergence of Markov chains using statistical values and visual illustrations. Statistically, the effective sample size (*n_eff*) and the Gelman–Rubin shrink factor (*Rhat*) can be used to assess the convergence. The *n_eff* value represents the number of iterative samples that are not auto-correlated during stochastic simulation, while the *Rhat* value is referred to as the potential scale reduction factor (Brooks & Gelman, 1998). If *n_eff* is larger than 1000, it is generally considered that the Markov chains are convergent, and the effective samples are sufficient for reliable inference (McElreath, 2018). As for the *Rhat* value, if the value exceeds 1.1, the model does not converge. The model is considered convergent if *Rhat* = 1. Visually, the Markov chains' convergence was also validated using trace plots, Gelman–Rubin–Brooks plots, and autocorrelation plots.

3. Results

Most respondents were middle-aged (41-50 years old: 36.67%), male (80%), married (78.33%), high school graduated (63.33%), private employee (60%), living with a spouse (cancer patients) and children (80%) with maximum GDP of IDR 5 million per month (68.34%).

Table 2. Demography Characteristic

No.	Characteristic	Frequency	Percentage
1	Age [years old]:		
	a. <21	2	3.33
	b. 21-30	7	11.67
	c. 31-40	15	25.00
	d. 41-50	22	36.67
	e. 51-60	10	16.67
	f. 61-70	4	6.67
2	Gender:		
	a. Male	48	80.00
	b. Female	12	20.00
3	Marital status:		
	a. Single	4	6.67
	b. Married	47	78.33
	c. Separated	2	3.33
	d. Divorced	1	1.67
	e. Widowed	6	10.00
4	Education level:		
	a. Primary school	6	10.00
	b. Secondary school	8	13.33
	c. High school	38	63.33
	d. University graduates	8	13.33
5	Occupation:		
	a. Housewife	12	20.00
	b. Entrepreneur	2	3.33
	c. Civil servant	6	10.00
	d. Private employee	36	60.00
	e. Jobless/retire	4	6.67
6	Gross Domestic Product (GDP) [IDR]:		
	a. Less than minimum wage	16	26.67
	b. Minimum wage – 5 million	25	41.67
	c. More than 5 million	15	25.00
	d. No income	4	6.67
7	Housemate:		
	a. Spouse	48	80.00

b. Child	48	80.00
c. Sibling	8	13.33
d. Parents	9	15

Almost all respondents reported unmet needs at various levels (98.33%), but the majority reported low levels of unmet needs (46.67%).

Table 3. The Level of Unmet Needs among FCG

No.	Categories	Frequency	Percentage
1	No need (45-90)	1	1.67
2	Low need (91-135)	28	46.67
3	Moderate need (136-180)	21	35.00
4	High need (181-225)	10	16.67

Before interpreting the results of BMF analytics, it is necessary to evaluate how well Model 1's fits the data. As can be seen in Figure 1, almost all estimated *k*-values are below the 0.5 threshold, and only one *k*-value is over the 0.5 threshold, indicating an acceptable fit signal between the model and the data.

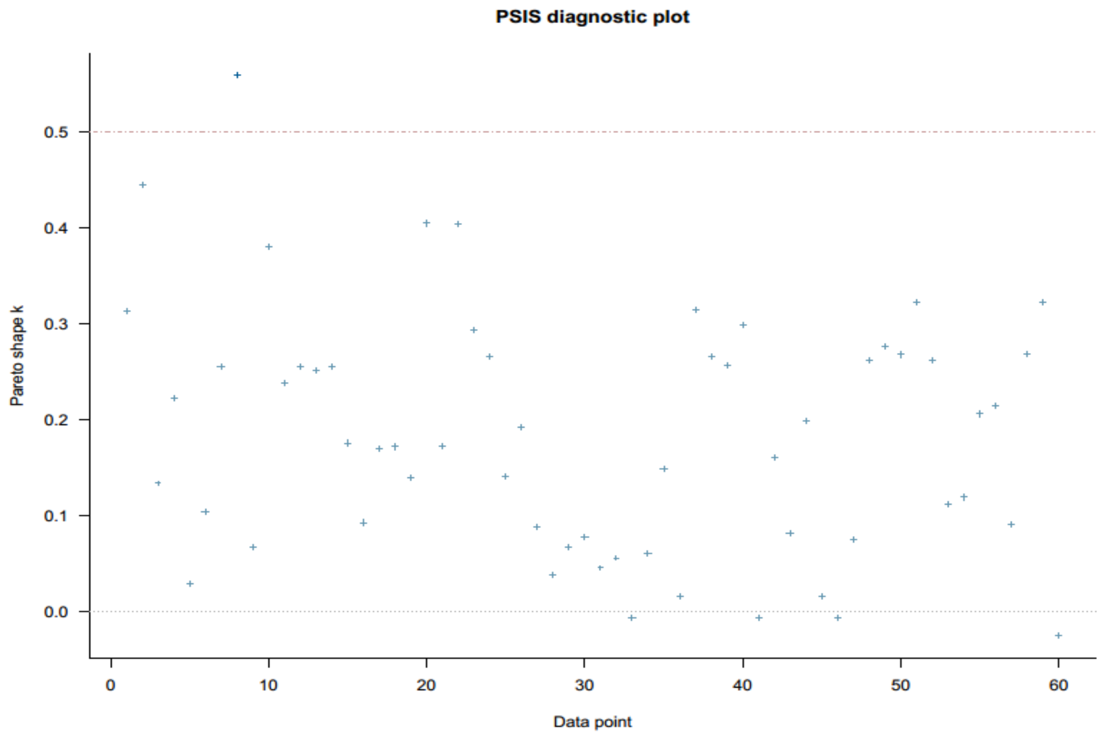

Figure 1. Model 1's PSIS-LOO diagnosis

The posterior distribution statistics of Model 1 are shown in Table 1. All *n_eff* values are greater than 1000, and *Rhat* values are equal to 1, so it can be assumed that Model 1's Markov chains are well-convergent. The convergence of Markov chains is also reflected in the trace plots of Figure 2. In particular, after the 2000th iteration, all chains' values fluctuate around the central equilibrium.

Table 4. Estimated results of Model 1

Parameters	Mean	SD	n_eff	Rhat
a_StressReduction	3.19	0.62	11056	1
b_Information_Caregiver_StressReduction	-0.06	0.27	9971	1
b_Information_Cancer_StressReduction	0.38	0.28	9773	1
b_Information_SupportServices_StressReduction	-0.40	0.24	11554	1
b_Information_AlternativeThe_StressReduction	-0.06	0.23	11651	1
b_Information_PhysicalNeed_StressReduction	0.14	0.22	11725	1
b_Information_SideEffects_StressReduction	-0.06	0.21	11406	1

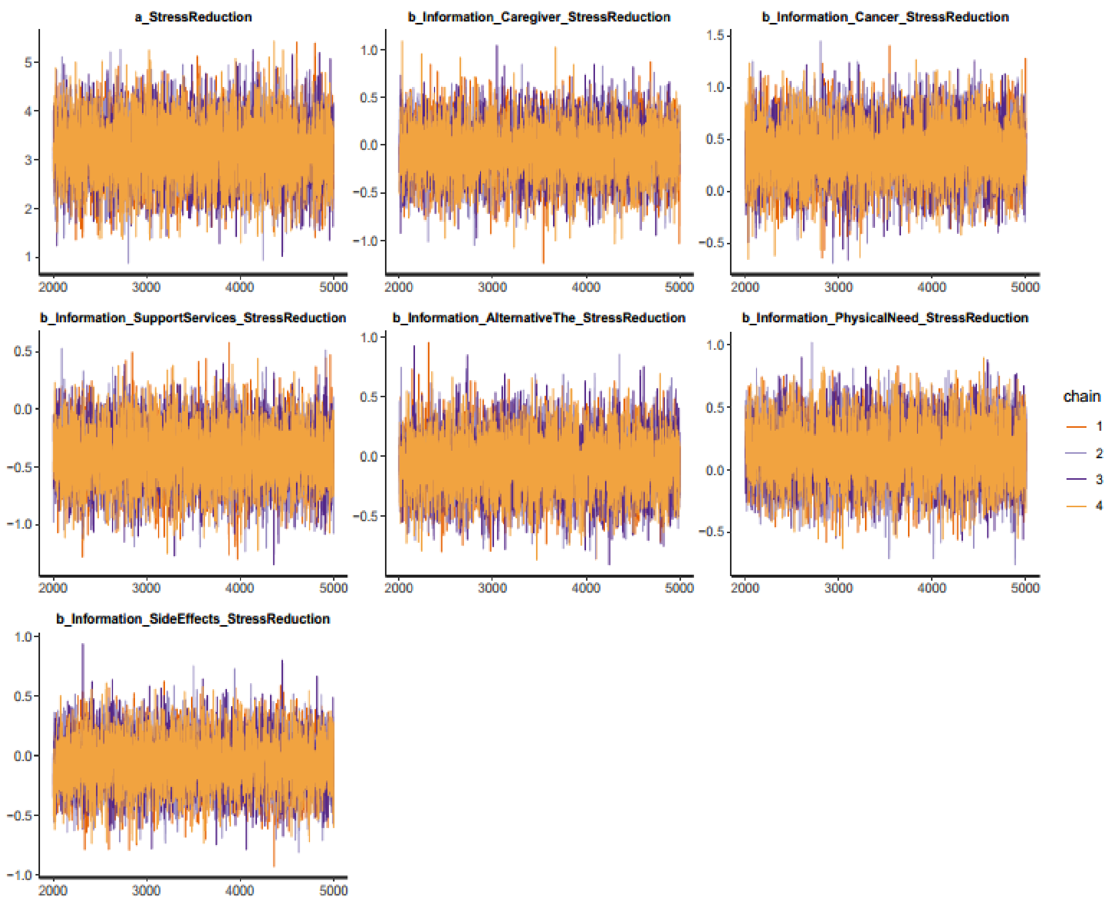

Figure 2. Model 1's trace plots

The Gelman-Rubin-Brooks and autocorrelation plots also show that the Markov chains converge well. Gelman-Rubin-Brooks plots help evaluate the ratio between the variance between Markov chains and the variance within chains. The *y*-axis demonstrates the shrinkage factor (or Gelman-Rubin factor), while the *x*-axis illustrates the iteration order of the simulation. In Figure 3, the shrinkage factors of all parameters rapidly decrease to 1 before the 2000th iteration (during warm-up). This manifestation indicates that there are no divergences between Markov chains.

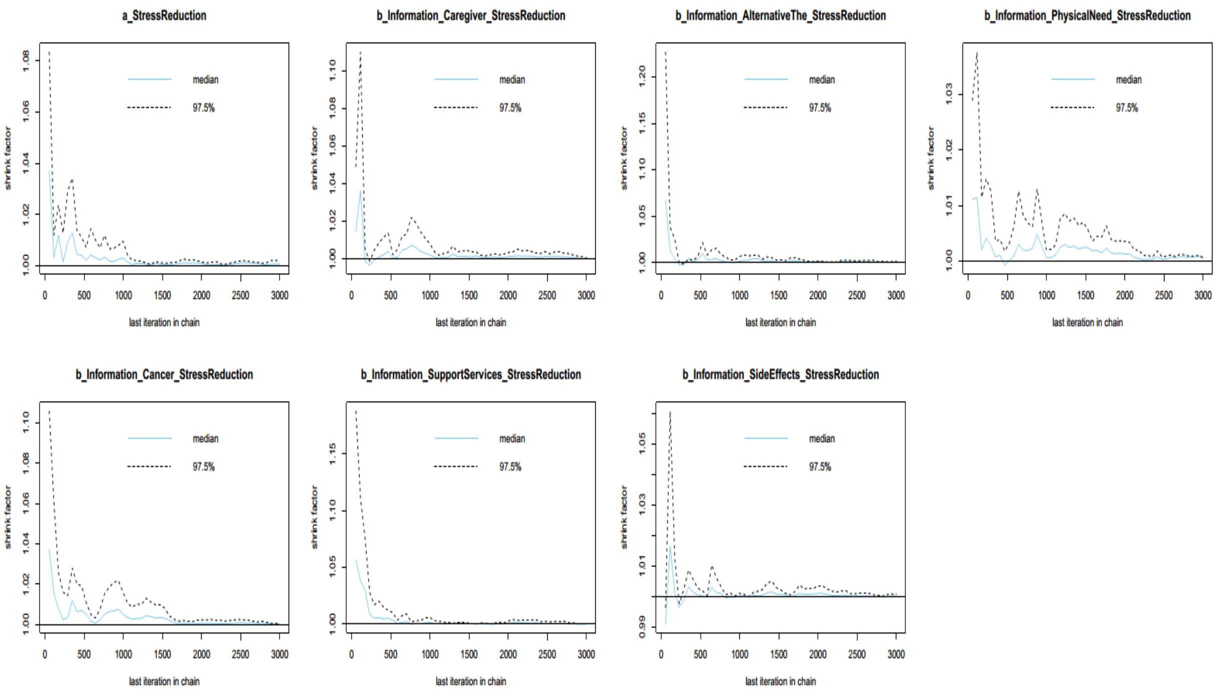

Figure 3. Model 1's Gelman-Rubin-Brooks plots

The Markov property refers to the memoryless property of a stochastic process. In other words, iteration values are not auto-correlated with the past iteration values. Autocorrelation plots are used to evaluate the level of autocorrelation between iteration values. The plots in Figure 4 show the average autocorrelation of each Markov chain along the y-axis and the delay of these chains along the x-axis. Visually, after several delays (before 5), the autocorrelation levels of all Markov chains swiftly drop to 0, indicating that the Markov properties are preserved and the Markov chains converge well.

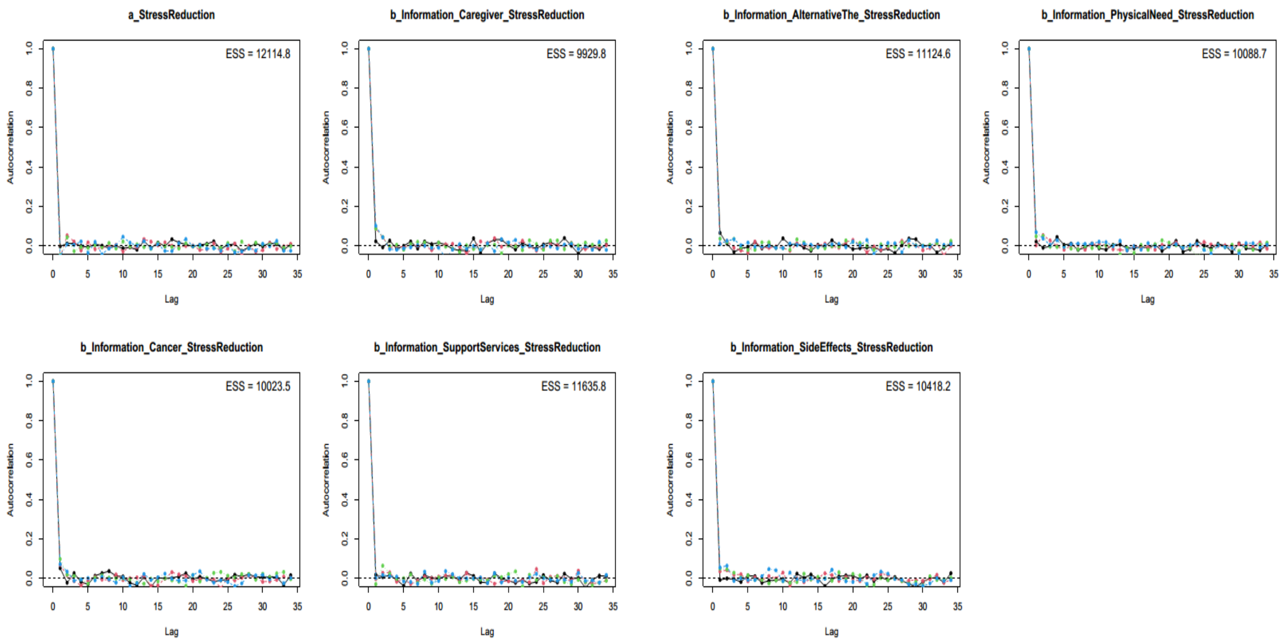

Figure 4. Model 1's autocorrelation plots

Since all the diagnostics confirm the convergence of Markov chains, the simulated results are eligible for interpretation. The estimated results of Model 1 show that among the six types of healthcare information, FCGs with a higher demand for cancer-specific information are more likely to need support in reducing the stress of female cancer patients. Meanwhile, FCGs with a higher demand for information on support services are less likely to need support in cancer stress management. Other types of information have ambiguous effects on the need for support in reducing cancer patients' stress. The posterior distributions of the two coefficients in Figure 5 lie entirely on the negative or positive side of the x-axis, indicating the high reliability of the results.

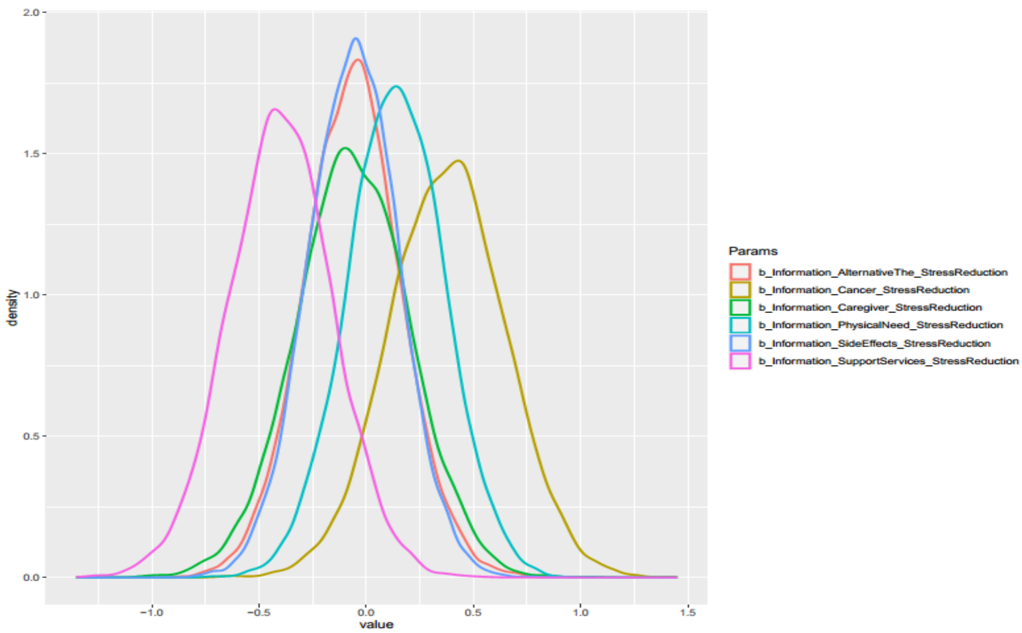

Figure 5. Model 1's posterior distributions

To aid result interpretation, Figure 6 illustrates the estimated outcomes based on estimated coefficients (using Mean values for computation, for they have the highest probability of occurrence). A majority of *b_Information_Cancer_StressReduction*'s distribution is located on the positive side, and a majority of *b_Information_SupportServices_StressReduction*'s distribution is situated on the negative side. These distributions signify the reliable positive effect of *Information_Cancer* and the negative effect of *Information_SupportServices* on *StressReduction*.

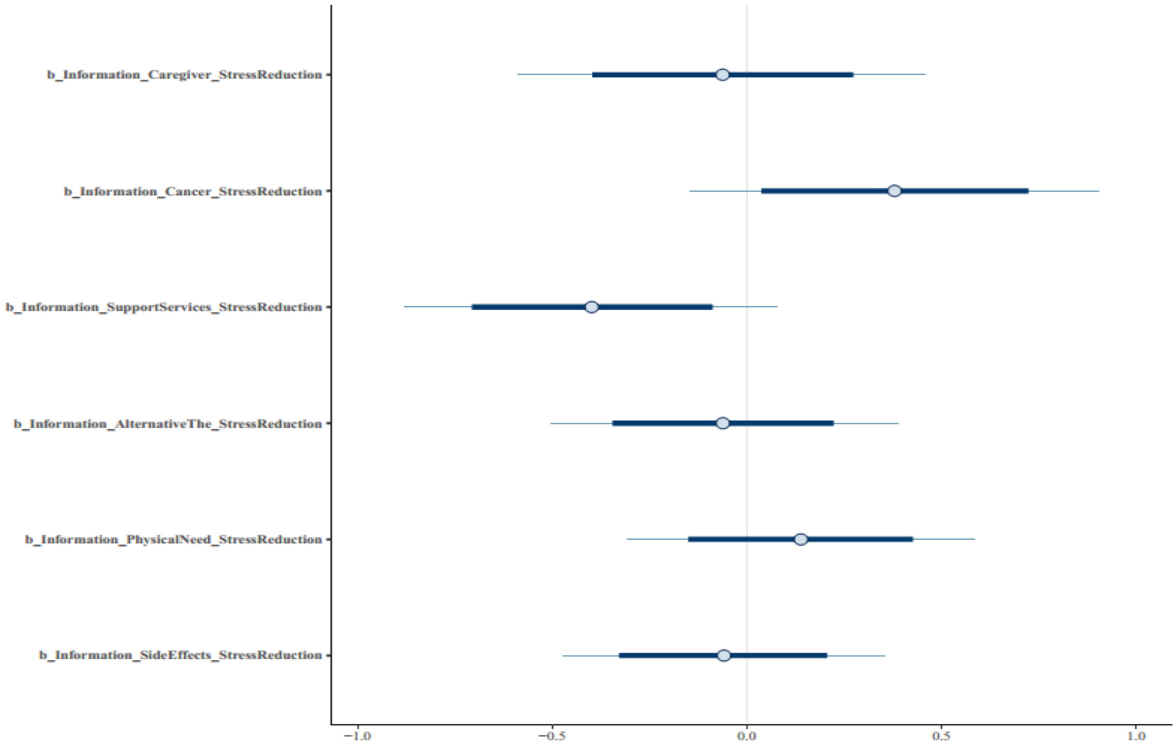

Figure 6. Estimated coefficients

4. Discussion

Employing the BMF Analytics on the dataset of spouses and family members regarding health care information revealed that FCGs with a higher demand for cancer-specific information are more likely to need support in reducing the stress of cancer patients than the ones with a higher demand for information on support services. These findings could be attributed to anxiety and depression, which have been reported to induce stress in cancer patients following diagnosis and treatment (Sari, 2020). Fear of diagnostic tests and the potential for malignancy to spread, return, and metastasis influence the perceived life normality of cancer survivors (Sari, 2020). These findings, to a greater extent, are in line with a study conducted by Ruiz-Rodríguez et al. (2021), which revealed that cancer patients' quality of life is severely jeopardized since the disease is commonly associated with death and suffering, stressful events and circumstances, and a decline in social, professional, personal, and family life for extended periods.

The finding that FCGs with a higher demand for information on support services are less likely to need support to reduce cancer patients' stress could be because families are regarded as the main support structures for patients. These findings are significant because family members, who often serve as a patient's primary support system, also act as extra listeners during doctor visits, which helps patients get the information they need (Ruiz-Rodríguez et al., 2021). In addition, family support is a crucial point of reference for cancer patients managing their stress. Studies have shown that patients' levels of stress management increase in direct proportion to their impression of family support (Ruiz-Rodríguez et al., 2021). Furthermore, throughout the whole period of cancer care, from the original diagnosis to treatment, remission, recurrence, long-term survivorship, and end-of-life care, FCGs serve as the primary healthcare professionals (Ferrell et al., 2019). Therefore, to help patients deal with the various emotional, psychological, social, and spiritual repercussions of cancer, education, and support of FCGs are essential, as reported by Ferrell et al. (2019).

The ambiguous effects of the other types of information on the need for support in reducing cancer patients' stress can be related to the differences in the needs of patients depending on the level of care desired. Chua et al. (2020) found that FCGs showed a greater tendency than patients to have unfulfilled needs, particularly concerning timely access to healthcare providers and physical, emotional, and psychological assistance. This emphasizes the necessary demands of the patients' FCGs to be met if it is set to provide cancer patients with high-quality care (Chua et al., 2020). Information on alternative therapies has been previously reported, particularly among stage 4 patients undergoing radiotherapy or chemotherapy (Chua et al., 2020). This is driven by hope for a cure and vulnerability to accessible alternative treatment methods, which may have dire consequences on the patient's health and well-being.

This study is not without limitations. The nature of the cross-sectional study has made the changing value of studied variables unmeasurable over time. This study may portray a certain situation at one time to show a pattern of events but may not show the dynamic changes of the situation in the field. The questionnaire used is a self-reported questionnaire by design. It might be less objective for measuring variables. Experimental studies with repeated measures using a more objective instrument must be conducted to address this study's limitations.

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