JOURNAL OF CONTENT VALIDATION 2026, VOL 2, ISSUE 2, 166-178
ISSN: 3093-8317, https://doi.org/10.67211, www.cvsgm.org

JOURNAL OF CONTENT VALIDATION ISSN: 3093-8317

Determinants of Wellbeing in Later Life: The Mediating Role of Social Support and Community Participation Among Seniors

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Received: 25 March 2025 • Accepted: 16 April 2026 • Published: 17 June 2026

Abstract

The growing aging population has increased the need to understand the factors that contribute to well-being in later life. Well-being among senior citizens is influenced by various social, psychological, and environmental determinants that shape their quality of life and overall life satisfaction. This study examines the determinants of well-being in later life, with particular emphasis on the mediating role of social support and community participation among senior citizens. A quantitative research design was employed in this study. Data were collected through structured questionnaire interviews from senior citizens residing in elderly care centers in Selangor, Malaysia. A total sample of respondents was selected using an appropriate sampling technique to ensure representativeness of the population. The collected data were analyzed using descriptive statistics and inferential analysis. Structural Equation Modeling (SEM) was applied to test the relationships among variables and to examine the mediating effects of social support and community participation. The findings of the study indicate that social support and community participation play a significant mediating role in enhancing well-being among older adults. These factors contribute to improved emotional stability, social connectedness, and overall life satisfaction in later life. The results further highlight the importance of supportive social environments and active engagement opportunities in elderly care settings. In terms of future research, it is recommended that studies expand the geographical scope beyond Selangor to include a more diverse elderly population across different regions and cultural contexts. Future studies may also incorporate longitudinal designs to better understand changes in well-being over time and explore additional psychological and environmental factors that may influence aging outcomes. Overall, this study contributes to the literature on aging and well-being by providing empirical evidence on the importance of social support and community participation in promoting successful and healthy aging.

Keywords: *Wellbeing; Later Life; Senior Citizens; Older Adults; Social Support; Community Participation; Active Aging; Quality of Life; Subjective Well-Being; Healthy Aging.*

INTRODUCTION

Population aging has emerged as one of the most significant demographic trends worldwide, bringing increased attention to the factors that influence well-being in later life. As individuals age, maintaining a high level of well-being becomes essential for ensuring a satisfactory quality of life, social integration, and healthy aging. Well-being in later life extends beyond physical health and encompasses psychological, emotional, and social dimensions that contribute to life satisfaction and overall happiness among senior citizens. Previous studies have identified various determinants that influence the well-being of older adults, including social relationships, access to support systems, and opportunities for active engagement within the community. Among these factors, social support and community participation have received considerable attention due to their significant contributions to the quality of life of senior citizens. Social support provides emotional, informational, and practical assistance that helps older adults cope with life challenges, reduce feelings of loneliness, and enhance their sense of security and belonging. Similarly, community participation enables older adults to remain socially connected, engage in meaningful activities, and maintain a sense of purpose and identity.

Despite the growing body of literature on elderly well-being, limited research has examined the mediating mechanisms through which social support and community participation contribute to well-being in later life. Understanding these pathways is important for developing effective interventions and policies that promote healthy and successful aging. Therefore, this study investigates the determinants of well-being in later life, with particular emphasis on the mediating role of social support and community participation among senior citizens.The study seeks to provide empirical evidence on how social support and community participation influence well-being among older adults. The findings are expected to contribute to the existing literature on aging and well-being while offering practical implications for policymakers, community organizations, and social service providers in designing programs that enhance the quality of life of senior citizens.

RESEARCH METHODOLOGY

This study employed a quantitative research approach to investigate the determinants of well-being in later life, with particular emphasis on the mediating role of social support and community participation among senior citizens. Quantitative research was considered appropriate because it allows for the systematic collection and analysis of numerical data, facilitating the examination of relationships among variables and the testing of proposed hypotheses.

The study was conducted in various elderly care centers located throughout the state of Selangor, Malaysia. Selangor was selected due to its relatively large elderly population and the availability of diverse elderly care facilities that accommodate senior citizens from different socioeconomic and cultural backgrounds. The target population consisted of approximately 9,000 senior citizens aged 65 years and above residing in registered elderly care centers across the state. A sample of 340 respondents was selected from the target population using an appropriate probability sampling technique to ensure adequate representation of the study population. The sample size was deemed sufficient based on established sample size determination guidelines for quantitative research and statistical analysis.

Data were collected through structured questionnaire interviews administered directly to the respondents. The structured questionnaire consisted of several sections covering demographic

characteristics, social support, community participation, and well-being in later life. Face-to-face interviews were conducted to ensure that respondents clearly understood the questions and to accommodate participants who might experience difficulties with self-administered questionnaires due to age-related limitations. Prior to the main data collection, the questionnaire was reviewed for content validity and clarity. Ethical considerations were observed throughout the research process, including obtaining informed consent from all participants, ensuring confidentiality of responses, and guaranteeing that participation was voluntary. The collected data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS) and Structural Equation Modeling (SEM). Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize the demographic characteristics and key study variables. Inferential statistical analyses were subsequently conducted to examine the relationships among the variables and to assess the mediating effects of social support and community participation on well-being among senior citizens.

DATA ANALYTICAL RESULTS

Data Cleansing

The data cleaning shown here is based on row data for the preparation of the study report chapter 4 for the actual study sample n = 340. Data cleaning through Multiple Imputation to confirm that all samples have answered all items and all evaluated variables have received a full response from the study sample. Findings from data cleaning through Multiple Imputation have shown that all 69 items or variables (variables) have been cleaned (100.0 percent) and the missing value is 0 percent.

Similarly, in terms of cases or respondents, a total of n = 340 people consisting of Formal and Informal Social Support were randomly selected for the purpose of the study. All study samples have also answered all the items given. The Missing Value box also shows that there are 23,460 data entries that have been keyed into the SPSS column, Patterns and Missing Value Patterns have also shown the same meaning. The blue color in the three circles for variables, cases and values indicates that all data has been filled in and cleared (no red color indicates data left to be filled). Based on figure 1 below it has been shown that all the study sample n = 340 items have answered all the items and have been cleaned from any blank or missing data.

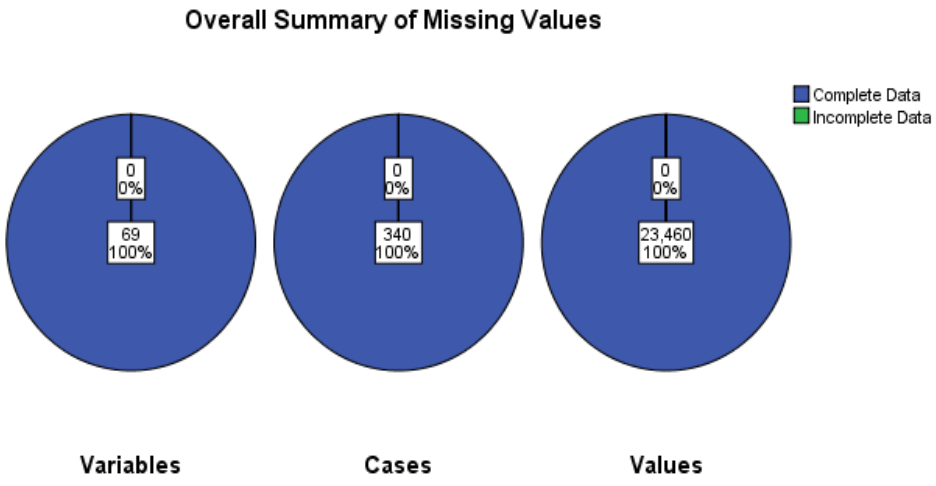

Figure 1 : Cleansing Data Through *Multiple Imputation*

Data Outliers

Outlier data refers to responses that differ significantly from the overall pattern of the dataset and may distort the accuracy of research findings if not properly addressed. Such extreme values may arise due to data entry errors or inconsistent responses, and therefore require careful examination before proceeding with statistical analysis. Identifying and handling outliers is an important step in ensuring data quality and maintaining the validity and reliability of the study results. Outliers are typically detected using graphical methods such as Boxplot analysis, where unusual cases may appear as isolated points outside the normal distribution range. A decision is then made whether to retain or remove these cases based on their relevance and accuracy. In this study, a total of 352 questionnaires were initially collected. After conducting data screening and identifying outliers using Boxplot analysis, 12 cases were removed, resulting in a final valid sample of n = 340. The final dataset was considered appropriate for further statistical analysis and hypothesis testing. This adjustment ensured that the dataset accurately represents the study population and improves the overall robustness of the analysis.

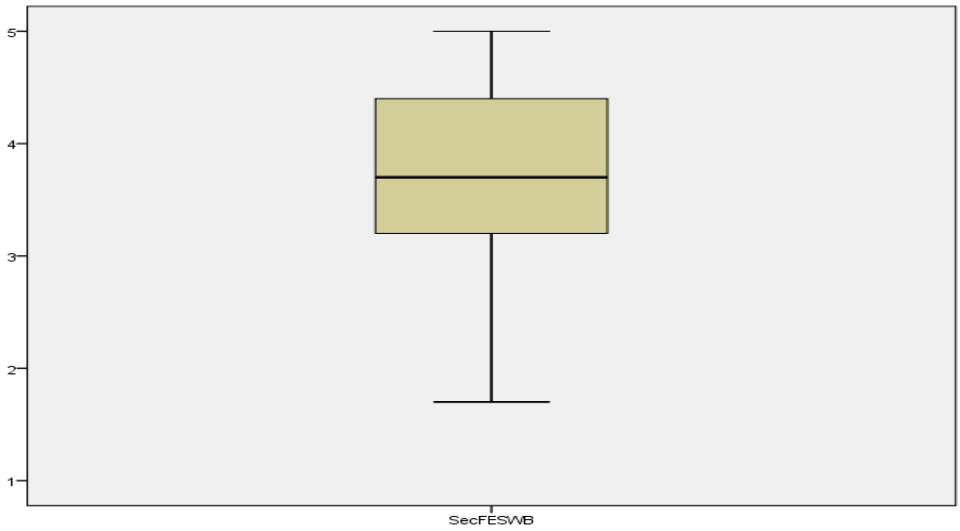

Figure 2 : Data Outliers

Normality Test

The normality test is conducted to determine whether the data are normally distributed, which is essential for deciding the appropriate statistical techniques for further analysis. If the data follow a normal distribution, parametric tests are applied; otherwise, non-parametric tests are considered. In this study, data normality was assessed using three approaches: visual inspection of the histogram bell curve, comparison of mean, median, and mode values, and evaluation of skewness and kurtosis values. These methods provide a comprehensive assessment of whether the dataset meets the assumptions of normality required for inferential statistical analysis.

According to established guidelines, skewness and kurtosis values within an acceptable range (typically between ±1.0 to ±3.0 depending on the reference standard) indicate that the data are approximately normally distributed. When skewness and kurtosis values are close to zero, the distribution is considered more symmetrical and closer to a perfect normal distribution. In this study, the results of the histogram showed a clear bell-shaped curve, while the mean, median, and mode values were closely aligned. In addition, the skewness and kurtosis values for all variables fell within the acceptable threshold,

indicating that the data were normally distributed. Therefore, it can be concluded that the dataset satisfies the assumptions of normality, and parametric statistical techniques are appropriate for further analysis.

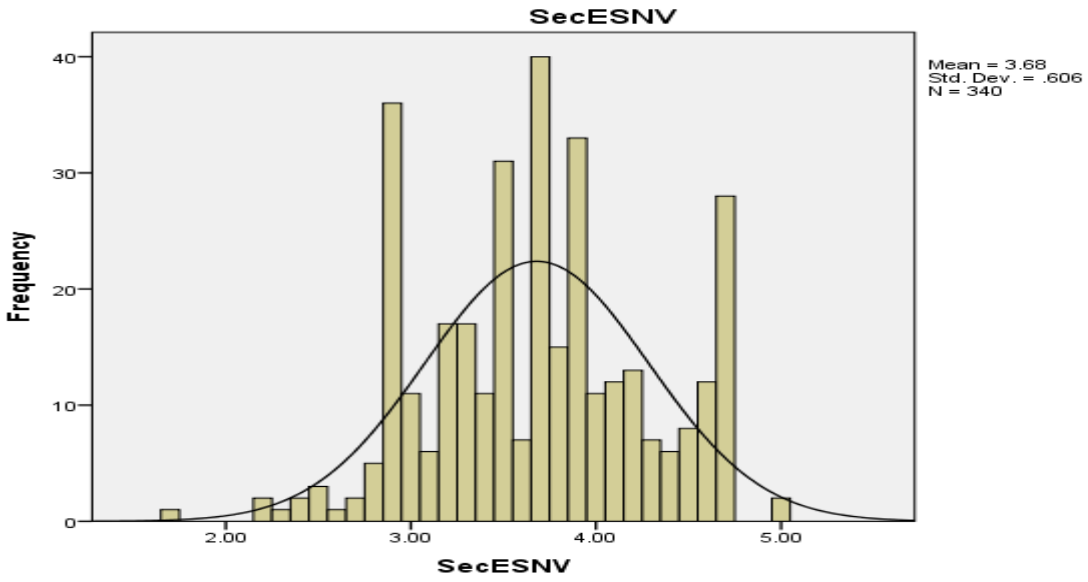

Figure 3: Data Normality Test Elderly Subjective Wellbeing

Demographic Report

The demographic data in this study consists of a randomly selected sample of n = 340 senior citizens residing in elderly care centers in Selangor, Malaysia. The profile includes gender, age, religion, race, education level, and marital status, and is analyzed using descriptive statistics (frequency and percentage). The results indicate that 47.9% (n = 163) of respondents were male and 52.1% (n = 177) were female. In terms of age distribution, the majority were aged 65–74 years (68.2%, n = 232), followed by 75–84 years (24.4%, n = 83), while a smaller proportion were aged 85–94 years (6.2%, n = 21) and 95 years and above (1.2%, n = 4). Regarding religion, most respondents were Muslim (85.6%, n = 291), followed by Buddhist (6.8%, n = 23), Hindu (5.3%, n = 18), and Christian (2.3%, n = 8). The ethnic composition shows Malay (63.5%, n = 216) as the largest group, followed by Chinese (22.1%, n = 75), Indian (12.6%, n = 43), and others (1.8%, n = 6). For education level, respondents reported primary education (28.8%, n = 98), secondary education (34.7%, n = 118), diploma (19.4%, n = 66), bachelor's degree (13.2%, n = 45), and postgraduate qualifications (3.9%, n = 13). In terms of marital status, 56.5% (n = 192) were married, 28.2% (n = 96) were widowed, 11.2% (n = 38) were divorced, and 4.1% (n = 14) were single.

Determining the structural model

The first step that researchers who want to use the PLS-SEM technique must do is to identify the study variables and then form a diagram that shows there is a relationship between the study variables or hypotheses (Hair, Hult, Ringle, & Sarstedt, 2017). This process will make it easier for researchers to identify the study variables as well as their relationship with other variables. At this stage, the research variable is no longer known as an independent variable or a dependent variable. The variables in the research model will be known as endogenous variables or exogenous variables.

In the research diagram, the endogenous variable is depicted as having at least one arrow pointing towards it, while the exogenous variable is depicted as having an arrow coming out of it and at the same time there is no arrow pointing toward it, the diagram is usually referred to as a path model or path model (Hair et al., 2017).

The path model consists of two elements. The first element is known as the structural model. The term structural model is also known as an internal model or inner model. A structural model explains the relationship between one latent variable and another latent variable. The second element is known as the measurement model. Apart from the term measurement model, it is also known as external model. The measurement model serves to provide information about the relationship between the latent variables and the study items.

According to Hair et al. (2017), in the structural model construction phase, two main issues that need attention. First, the sequence of study variables and the second is their relationship to each other. These two points are worth noting because they represent tested hypotheses and theories. Sequences or variables must be based either on theory, logic or the researcher's experience. According to Hair et al. (2017) again, the order of study variables is usually arranged from left to right. The independent variable is placed on the left and the dependent variable is placed on the right. Therefore, it can be concluded that the exogenous variable will be on the left and on the other hand the endogenous variable will be on the right. Variables that function as exogenous and at the same time also act as endogenous will be in the middle.

Determining the Measurement Model

The second step is to define the measurement model. The measurement model involves the relationship between latent variables and study items. The basic thing that needs to be there to determine the measurement model is measurement theory. According to Hair et al. (2017), hypothesis testing will only be conducted if the measurement model reaches the desired level of reliability and validity. In reality, many researchers today use questionnaires found in past studies that have been certified for reliability and validity. However, Hair et al. (2017) stated that some researchers face problems in obtaining quality questionnaires.

Concerning that, they need to develop a new questionnaire or at least modify the existing questionnaire. However, the process of developing a new questionnaire is very long, complicated and complicated. Another thing that researchers need to focus on is the issue of whether the measurement model is reflective or formative. In the study of Diamantopoulos, Riefler, & Roth (2008), they have identified the consequences of the researcher's negligence in determining whether the research variables are formative or reflective. Among the consequences that may be faced by researchers is the problem of bias parameters and the effect on adjustment statistics or fit statistics (Diamantopoulos et al., 2008).

Assessing Measurement Model

According to Hair et al. (2017) before evaluating the structural model it is appropriate to discuss the nature of the construct and the type of measurement model involved. The measurement model of a construct can be classified into two, namely either a formative measurement model or a reflective

measurement model. In the reflective measurement model, all relationships are from constructs to indicators. This shows that the construct that determines the indicator. While for the formative measurement model, the relationship is from indicator to construct. This shows that the construct has been explained by the indicator.

However, many researchers tend to make mistakes when specifying the constructs due to the lack of attention given to the specification of the measurement model (Jarvis, MacKenzie, & Podsakoff, 2003). Thus, it will have an impact on the developed model. To address the problem, Jarvis et al. (2003) have outlined four guidelines for deciding whether a measurement model is reflective or formative. Thus, this study has adapted the guidelines in determining the type of measurement model to be used. Before answering all the research questions, the researcher first made the validity of the study through the CFA (measurement model). The measurement model in this study was tested with confirmatory factor analysis. The exploratory factor analysis approach was not used because the study items were adapted from established theories (Hurley et al., 1997). Because the measurement model in the study is in the form of Mode A (reflective), then this measurement model has been measured based on the reflective model evaluation method found in the literature.

Construct validity testing is conducted through the assessment of convergent validity and discriminant validity. A variable is considered to have convergent validity if three criteria are met, first, the factor loading value of all individual items must exceed 0.708. However, items that have factor loading values between 0.4 to 0.7 can be considered to be retained (Hair, Hult, Ringle, & Sarstedt, 2017). Based on the findings of the pilot study, it was found that some items have factor loading values that are less than 0.708 but those items are retained because removing the item (in bold) does not increase the AVE value and composite reliability of the construct in question (Hair et al., 2017). Second, the composite reliability value is not less than 0.6 and thirdly the AVE value must be above 0.5 (Fornell and Larcker, 1981). The pilot study data showed that each study variable met the required criteria. However, some items had to be discarded because they had too low factor loading values. All items removed are from the construct which is 26 items. The discriminant validity is met if the root value of the AVE is greater than the correlation value of the latent variable (Fornell and Larcker, 1981).

Discriminant Validity

Then in step 2, we assessed the discriminant validity using the HTMT criterion suggested by Henseler et al. (2015) and updated by Franke and Sarstedt (2019). The HTMT values should be $\leq$ 0.85 the stricter criterion and the mode lenient criterion is it should be $\leq$ 0.90. As shown in Table 4.5, the values of HTMT were all lower than the stricter criterion of $\leq$ 0.85 as such we can conclude that the respondents understood that the 9 constructs are distinct. Taken together both these validity test has shown that the measurement items are both valid and reliable.

Common Method Bias

Tackling collinearity from the beginning enables researchers to mitigate related problems, leading to a stronger, more reliable, and easier-to-understand structural model that accurately represents the

connections between variables. To effectively address collinearity, one can utilize techniques like variance inflation factor (VIF) analysis, feature engineering, or variable subset selection.

Table 1: Common Method Bias

Construct	VIF
ESW	1.777
ECI	1.021
SS	1.779

Since data was collected using a single source, we first tested the issue of Common Method Bias by following the suggestions of Kock and Lynn (2012), and Kock (2015) by testing the full collinearity. In this method all the variables will be regressed against a common variable and if the VIF ≤ 3.3 then there is no bias from the single source data. The analysis yielded VIF less than 3.3 thus single-source bias is not a serious issue with our data (see Table 1).

Table 2: Hypothesis Testing

HYPO		Beta value	mean (M)	STDEV	T Value	P value	Result
H1	ECI -> ESW	-0.219	-0.146	0.133	1.649	0.099	Supported
H2	SS-> ESW	-0.088	-0.093	0.074	1.198	0.091	Supported
H4	ECI x SS-> ESW	-0.002	0.007	0.065	1.235	0.972	Supported

Goodness of Fit (GoF)

In this study, the outcome of the GoF analysis is shown in Table 2; both SRMR and NFI values are within acceptable range and confirm model fitness. Acceptable range for SRMR is within 0.08, and for the Normed fit index (NFI), it is within 0.90.

Table 3: Goodness of Fit (GoF)

	Empirical model
SRMR	0.070
NFI	0.504

Coefficient of determination (R^2)

The next step in evaluating the structural model is to calculate the level of R^2 (Coefficient of Determination). This coefficient is a measure of model strength, measured based on the R^2 value obtained through the PLS Algorithm procedure (Mcintosh et al., 2014). It is the squared relationship between the actual and predicted values. It also refers to the amount of variance in an endogenous construct explained by the exogenous construct associated with it (Hair et al., 2017; Shmueli & Koppius, 2011). In other words, the strength of the model aims to assess the degree of change that occurs to the dependent variable when the independent variable is included in the analysis. It is considered a measure of predictive power in the sample.

R^2 values range from 0 to 1, with higher levels indicating higher levels of model prediction accuracy (Hair et al., 2019). It is difficult to practically determine an acceptable R^2 value because this depends on the complexity of the model and the context of the study (Hair et al., 2019). Raithel et al.

(2012) in the same tone stated that the acceptable R^2 value is based on the context and in some disciplines with an R^2 value as low as 0.10 is considered satisfactory, for studies related to social sciences, the recommended R^2 value is R^2=0.26 which is categorized as robust, 0.13 as moderate and 0.02 as weak (Cohen, 1988). However, Hair et al. (2017) and Henseler et al. (2009) suggested that an R^2 value of 0.75 is categorized as strong, 0.50 as moderate and 0.25 as weak. Table 4 shows the results of R^2. Hence, this study obtains moderate R^2.

Table 4: Coefficient of determination (R^2)

Hypothesis		**R^2**
H1	ECI -> ESW	0.201
H2	SS -> ESW	

Effect size (f^2)

Next, the fourth step is testing the structural model by calculating the effect size (f^2). In addition to evaluating the value of R^2 in the endogenous construct, changes in the value of R^2 can also occur when certain exogenous constructs are removed from the model, then the evaluation of the effect size (f^2) can be used to assess whether the removed construct has a significant effect on the endogenous construct (Hair et al., 2022). In other words, the effect size (f^2) is measured to assess the level of contribution of exogenous variables (independent variables) over endogenous variables (dependent variables) (Nitzl et al., 2016). Guidelines for evaluating f^2 are values of 0.02, 0.15, and 0.35, representing small, medium, and large effects of the exogenous variable, respectively (Cohen, 1988; Hair et al., 2017). An effect size value of less than 0.02 indicates that there is no effect (Hair et al., 2022). Table 5 below shows the results of f^2 values.

Table 5: Effect size (f^2)

Constructs	**f^2**
ECI	0.010
SS	0.001
ESW	0.002

Table 4.11 displays the effect size value f^2, showing that the exogenous variable SNV has a medium effect size of 0.221, meanwhile, the other exogenous has a small effect size.

Conclusion

This study examined the determinants of wellbeing in later life with a particular focus on the mediating role of social support and community participation among senior citizens residing in elderly care centers in Selangor, Malaysia. Based on a quantitative research design, data were collected through structured questionnaire interviews from a valid sample of respondents and analyzed using descriptive and inferential statistical techniques. The findings of the study highlight that wellbeing in later life is significantly shaped by the availability and quality of social support as well as the level of community participation among older adults. These two factors play an important mediating role in enhancing the overall well-being of senior citizens by strengthening their social connections, reducing feelings of isolation, and improving their sense of belonging and life satisfaction. The results also confirm that the data met the assumptions of normality, allowing the use of appropriate parametric statistical methods for hypothesis testing.

Overall, the study contributes to a better understanding of how social and community-based factors influence the well-being of elderly individuals. It emphasizes the importance of fostering supportive social environments and encouraging active participation in community activities within elderly care settings. The findings provide valuable insights for policymakers, care providers, and social welfare organizations in developing targeted interventions and programs aimed at promoting healthy and successful aging. In conclusion, enhancing social support systems and increasing opportunities for community participation are essential strategies for improving the quality of life and well-being of senior citizens. This study underscores the need for continued attention to social integration as a key component of elderly care and well-being promotion.

Acknowledgement

We would like to express our sincere gratitude to all co-authors for their continuous guidance, valuable insights, and intellectual contributions throughout the development of this research. Their collaborative efforts and academic support have been instrumental in shaping the direction and quality of this study. We also extend our heartfelt appreciation to all the institutions and elderly care centers in Selangor, Malaysia, that generously granted permission and facilitated the data collection process. Without their cooperation and support, the successful completion of this study would not have been possible. Special thanks are due to the heads of the respective institutions and care centers for their kind approval, assistance, and encouragement during the fieldwork. Their willingness to support academic research and provide access to respondents played a crucial role in ensuring smooth and effective data collection. Finally, we acknowledge all the senior citizens who participated in this study. Their time, cooperation, and willingness to share their experiences are deeply appreciated and form the foundation of this research.

Funding: The research did not receive financial assistance from any funding entity.

Conflicts of Interest: The author has no conflicts of interest to disclose concerning this study.

Declarations: This manuscript has not been published to any other journal or online sources.

Data Availability: The author has all the data employed in this research and is open to sharing it upon reasonable request.

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