Predicting Loneliness in Thailand: A Nationwide Cross-Sectional Analysis of Health, Socio-Demographic, and Geographical Factors

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Abstract
This nationwide cross-sectional study investigates the health, socio-demographic, and geographical determinants of loneliness among the adult population in Thailand. Data were collected from a cohort of 714 Thai adults between August 2024 and November 2025 using the "TiS-MSU" telehealth platform and a network of community health volunteers. Loneliness was measured using the UCLA Loneliness Scale. Statistical analysis included descriptive statistics to profile the sample, bivariate testing to explore associations, and multiple linear regression to identify significant predictors. Descriptive analysis indicated that 65.41% of participants reported feeling no loneliness. However, inferential analysis revealed significant demographic disparities: males and LGBTQ+ individuals reported higher levels of loneliness compared to females. Multiple linear regression ($R^2 = 0.27$, $p < .001$) identified age as a significant negative predictor, suggesting that younger adults are more susceptible to loneliness. Employment status also emerged as a critical factor ($p = .01$), with both employees and the unemployed reporting higher levels of loneliness than civil servants. Notably, married participants reported higher loneliness scores than those who were single, divorced, or widowed ($p < .01$). Geographically, higher levels of loneliness were concentrated in Bangkok and its surrounding metropolitan areas. In contrast, the lowest levels were observed in southern Thailand. These findings highlight the need for targeted mental health interventions and psychological support frameworks specifically designed for younger populations, employed individuals, and residents of high-density urban areas. The results emphasize the complex interplay between socio-demographic factors and regional environments in shaping the psychological well-being of the Thai population.

Keywords: Assisted Living, Bangkok Metropolitan Area, Elderly Care Centers, Foreign Retirees, GIS, Health Promotion Model, Self-Efficacy, Spatial Health Planning

1. Introduction

Thailand is rapidly transitioning into an aging society, which is contributing to a rise in non-communicable diseases (NCDs) and mental health challenges [1]. One significant issue that has emerged is loneliness, which is linked to negative health outcomes such as cardiovascular disease [2], depression, and cognitive decline [3] and [4]. While many factors contributing to loneliness have been thoroughly studied in Western contexts, there is a notable lack of comprehensive nationwide research focused specifically on the Thai population. Loneliness is a complex concept that has been explored across different populations using various assessment methods. A substantial body of research indicates a reciprocal relationship between loneliness and depression [5]. For instance, studies have shown that persistent negative thoughts about loneliness can predict depressive symptoms over time [6].

In addition to its connection to depression, loneliness is recognized as a factor contributing to social impairment associated with conditions such as schizophrenia. Technologies such as smartphone sensing have been used to analyze social behavior in this context [7]. The impact of social connections and isolation on loneliness is a recurring theme in the literature. Researchers have also investigated the relationships among loneliness, social support, and language use, examining aspects such as pronoun use and sentiment to identify social isolation among older adults [8][9] and [10] Moreover, lifestyle factors, including physical activity levels and health behaviors, are also considered in loneliness research [11]. Various data collection methods have been employed in these studies, including surveys, smartphone data, and linguistic analysis [10] and [12] Research has shown that changes in cortisol levels are associated with feelings of loneliness during periods of social isolation [13].

Advancements in neuroimaging techniques, particularly resting-state functional magnetic resonance imaging (fMRI) [14], have significantly deepened our understanding of loneliness by revealing specific brain connectivity patterns associated with this emotion [15] and [16] Some studies have even proposed machine learning models to predict individual levels of loneliness based on these identified patterns of brain connectivity [17]. The foundation of Thailand's primary healthcare system relies on more than one million Village Health Volunteers (VHVs), known locally as "Aor Sor Mor." These volunteers play a crucial role in linking communities to the formal health system. To enhance their capabilities, the "Telehealth in Strengthening Community Health Volunteer System in Thailand (TiS-MSU)" project was launched. This initiative uses a LINE Official Account and a website to facilitate nationwide health data collection by VHVs.

This study leverages the data infrastructure provided by the TiS-MSU project to conduct the first nationwide analysis of factors predicting loneliness in Thailand. By collecting comprehensive data on health metrics, socio-demographics, and geographical locations, we aim to answer the key research question: What are the most significant factors predicting self-reported loneliness among adults in Thailand? Identifying these factors is a crucial first step in developing targeted, evidence-based public health strategies to reduce loneliness and improve the well-being of the Thai population.

2. Literature Review

2.1 Definition, Contributing Factors, and Consequences of Loneliness

This highlights the evolving understanding of loneliness, which is inherently subjective and can be defined in various ways. The factors contributing to loneliness can be both social and individual, encompassing a wide range of risks and causes. This complexity underscores the need for diverse approaches to address loneliness effectively [18] and [19]. Loneliness is a profound emotional state that significantly impacts overall well-being, making it an important topic of research in health sciences. It is fundamentally understood as a subjective psychosocial condition characterized by a perceived discrepancy between an individual's desired and actual social relationships [20] and [21] While it is a deep emotional experience, loneliness is not formally classified as a psychiatric disorder or a clinical mental illness in standard diagnostic frameworks such as the DSM-5.

However, despite not being categorized as a distinct mental illness, a substantial body of research indicates a reciprocal relationship between chronic loneliness and severe psychological issues. Recent clinical reviews demonstrate that loneliness is highly prevalent among individuals with personality disorders, sharing underlying intra- and interpersonal vulnerabilities such as heightened rejection sensitivity, information processing biases, and social withdrawal that mutually reinforce and exacerbate the severity of overall psychopathological symptoms [22].

Furthermore, loneliness can stem from various factors, including negative experiences with peers, socioeconomic challenges, living conditions, health status, and perceptions of aging. The consequences of loneliness are serious and range from an increased risk of mental health issues, such as depression and anxiety, to declining physical health and engaging in risky behaviors. In older adults, loneliness is specifically linked to a higher risk of frailty and cognitive decline, including Alzheimer's disease [23]. Consequently, while loneliness remains a subjective feeling of existential isolation rather than a formal disease, it is increasingly recognized by healthcare professionals as a vital public health indicator that requires targeted interventions to prevent the onset of clinical psychiatric outcomes.

2.2 Interconnectedness of Social Isolation and Future Research Directions

Social isolation and loneliness are often interconnected, as a lack of social connections can lead to the development and persistence of loneliness [18] Interventions aimed at enhancing social connections and reducing isolation have shown promise in decreasing loneliness and its associated risks. Despite notable progress in understanding loneliness, there is still much to discover. Research across various age groups, cultures, and social contexts is essential for creating targeted interventions and preventive measures [24] and [25]. Additionally, exploring the interplay of biological, psychological, and social factors related to loneliness could deepen our understanding and lead to more effective treatments. Loneliness can manifest as a profound sense of existential isolation. Existential loneliness is characterized by a deep feeling of separation from others and the universe, often accompanied by emotions of alienation, emptiness, and abandonment.[26] Healthcare professionals have an ethical responsibility to recognize and address these experiences in their patients through compassionate communication and support.

2.2.1 Loneliness and social media use

The relationship between social media use and loneliness is complex. A study examining this relationship among medical students found that while social media can foster connections, it can also lead to feelings of loneliness, particularly among younger users [27]. The study emphasizes the importance of understanding how different social media platforms and usage patterns affect self-esteem, body image, and experiences of loneliness.

2.2.2 Health consequences of loneliness

Loneliness can have a profound impact on both mental and physical health. A meta-analysis has shown that loneliness significantly affects various health outcomes, including mental health, self-rated health, overall well-being, physical health, sleep, and cognition [28]. These findings highlight the importance of addressing loneliness as a critical public health issue. Loneliness, which is defined as a subjective feeling of isolation, disconnection, and a lack of belonging in social relationships, has emerged as a significant public health concern in Thailand. This literature review examines the prevalence, contributing factors, and consequences of loneliness across different populations in Thailand.

2.3 Measurement and Predictive Gaps in Loneliness Research

2.3.1 UCLA loneliness scale

While several studies have assessed loneliness using validated tools such as the UCLA Loneliness Scale and its variants, none of the reviewed studies directly examined general predictors of loneliness. Previous research has examined the relationship between loneliness and other factors, including depressive symptoms, social interactions, and sleep patterns [29]. However, these studies did not focus on features designed explicitly for prediction.

2.3.2 The loneliness in intimate relationships scale (LIRS)

Recently, one study developed a new self-report scale, the Loneliness in Intimate Relationships Scale (LIRS), to measure loneliness within intimate relationships [30]. This scale captures specific features, such as detachment, hurt, and guilt, but it does not aim to predict loneliness more broadly. Additionally, [31] developed the Revised UCLA Loneliness Scale (RULS-6), a concise version derived from the original UCLA Loneliness Scale. These advancements contribute to a more nuanced and culturally sensitive understanding of loneliness across diverse populations and relationship contexts.

2.3.3 The De Jong Gierveld loneliness scale

In contrast, the De Jong Gierveld Loneliness Scale distinguishes between emotional and social loneliness, offering a more nuanced understanding [32]. While it also demonstrates strong psychometric properties, its multidimensional nature may complicate administration and scoring processes.

2.4 The Role of Artificial Intelligence and Natural Language Processing in Predicting Loneliness

Artificial intelligence (AI) and natural language processing (NLP) were used to analyze speech patterns and identify loneliness in older adults, with a model achieving 88.9% accuracy. This demonstrates AI's potential to detect loneliness and deepen our understanding of its underlying mechanisms [9]. While existing loneliness scales are useful assessment tools, further research is needed to enhance their cultural sensitivity and predictive validity. Future studies should focus on validating these scales in diverse cultural contexts to ensure their relevance and accuracy.

Although existing loneliness scales are useful assessment tools, further research is needed to enhance their cultural sensitivity and predictive validity. Future studies should aim to validate these scales across diverse cultural contexts to ensure their relevance and accuracy. Recent applications of machine learning in Thai communities illustrate that predicting loneliness involves examining a complex interplay of functional and psychological variables, in addition to basic demographics [33]. Additionally, investigating potential predictive factors, such as physiological markers, neuroimaging data, pet ownership, patterns of repetitive negative thinking, and digital footprints, could improve the early identification and intervention for loneliness. It is also crucial to develop targeted interventions that address the specific needs and challenges of various populations experiencing loneliness, thus maximizing their effectiveness and cultural appropriateness. The study of loneliness is an evolving field. By refining existing tools, exploring new measurement methods, and developing tailored interventions, researchers can enhance our understanding of loneliness and improve the well-being of individuals and communities.

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3. Methodology

This research employs a mixed-methods approach for data collection [18], utilizing both online and offline platforms to engage a diverse population in Thailand. The online component will leverage LINE OA, a popular messaging app in the country, to develop chatbots and interactive tools that enhance user engagement and facilitate data collection. This method increases accessibility and convenience, especially for individuals experiencing loneliness, who may find it easier to interact with a chatbot than to complete a traditional survey [34]. The offline component will feature a dedicated website that hosts surveys and questionnaires tailored to the research objectives. This strategy enables more in-depth data collection and the exploration of a broader range of topics related to loneliness. Throughout the data collection process, ethical considerations will be prioritized, including data privacy and informed consent, to protect participants' rights and well-being [35] and [36].

3.1 Study Design and Participants

A nationwide cross-sectional study was conducted using the TiS-MSU platforms from August 2024 to November 2025, involving adults aged 18 and older residing in Thailand. Village Health Volunteers (VHVs) facilitated enrollment via the "TiS-MSU" telehealth platform. A total of 714 individuals from a local community were recruited to participate in this study, which assessed the risk of loneliness. The participants were categorized into three self-identified gender groups: females (N=477), males (N=227), and LGBTQ+ individuals (N=10). The demographic composition revealed that the sample was predominantly female, comprising 66.8% of the total, while males accounted for 31.8% and LGBTQ+ individuals represented 1.4%. Data on self-perceived loneliness levels were collected from this sample to analyze the prevalence and distribution of loneliness across these gender demographics. The UCLA Loneliness Scale was consistently used for all loneliness assessments in this study.

3.1.1 Phase 1: Descriptive analysis

The initial phase of quantitative analysis begins with a comprehensive descriptive statistical summary that establishes the sample's foundational characteristics. The primary goal is to provide a clear overview of participant demographics and the distribution of key variables. This descriptive summary consists of two components. First, for categorical variables such as gender, self-reported loneliness levels, work status, and marital status, a frequency analysis is conducted. This involves calculating absolute counts (N) and relative percentages (%) for each subgroup to highlight the sample's composition and distribution. Second, for continuous variables like participant age or standardized loneliness scores (e.g., the UCLA scale), essential descriptive statistics are calculated. These include measures of central tendency (mean), dispersion (standard deviation), and the range (minimum and maximum values). Together, these statistics offer a foundational understanding of the "average" participant and the variability within the dataset.

3.1.2 Phase 2: Bivariate analysis (identifying relationships)

The second phase of the analysis follows the initial descriptive summary and involves a bivariate examination to test the association between each independent variable and the outcome of loneliness. This step aims to identify which factors (e.g., gender, work status) are statistically associated with loneliness when assessed individually, thereby helping isolate potential predictors for later inclusion in a multivariable model. The choice of statistical test depends on the measurement level of the variables. For two categorical variables (such as "Gender" and "Loneliness Level," which includes categories like "Feel Lonely" and "Not Lonely"), a Chi-Square (χ^2) test of independence is utilized. This test determines whether the observed frequency distribution is statistically significant or likely due to chance. To compare the means of a continuous "Loneliness Score" between two groups (e.g., males and females), an independent-samples t-test is used. For categorical variables with three or more groups (such as different gender categories or work statuses), a one-way ANOVA is employed. Additionally, the relationship between two continuous variables (e.g., "Age" and "Loneliness Score") is assessed using Pearson's correlation coefficient (r), which measures the strength and direction of their linear relationship. Completing this phase provides a comprehensive list of statistically significant factors that will serve as the foundation for the final predictive model.

3.1.3 Phase 3: Multivariable regression analysis (identifying risk)

The final analytical phase consists of conducting a multivariable analysis to identify the most significant predictors of loneliness risk. This approach is crucial because it statistically controls for confounding effects among interrelated variables (for example, the strong association often observed between age and marital status) that simple bivariate tests cannot account for. The objective is to determine the unique predictive value of each factor while considering the influence of all other variables in the model. A multiple linear regression model is recommended, particularly when the dependent variable is continuous, such as a composite score derived from the UCLA Loneliness Scale. In this context, the loneliness score acts as the dependent variable. In contrast, the independent variables include all factors assessed in the preliminary analysis, such as gender, age, marital status, work status, and living arrangement. The model's interpretation relies on three primary metrics. The coefficient of determination (R^2) indicates the model's overall explanatory power by showing the percentage of variance in loneliness scores attributable to all predictors combined. The standardized beta coefficient (β) conveys the unique effect of each predictor variable while keeping other variables constant.

3.2 Research Framework and Workflow

This study employs a comprehensive four-stage research framework to systematically capture and analyze the multidimensional factors that contribute to loneliness as illustrates in Figure 1.

Stage 1: Data Acquisition involves leveraging the "TiS-MSU" telehealth infrastructure. We utilize both online (through LINE Official Account chatbots) and offline channels, facilitated by Village Health Volunteers (VHVs), to secure a nationwide, cross-sectional cohort of 714 Thai adults.

Stage 2: Variable Operationalization standardizes the input data by extracting key health metrics, socio-demographic profiles, geographic coordinates, and the primary dependent variable, which is measured using the UCLA Loneliness Scale.

Stage 3: Statistical Modeling follows a hierarchical analytical pipeline. It begins with descriptive profiling of the sample, progresses to bivariate association testing to isolate individual statistical relationships, and concludes with multivariable linear regression to identify unique risk predictors while controlling for confounding effects.

Stage 4: Geospatial Visualization integrates the statistical outputs with regional coordinate data to create high-resolution choropleth and point-density maps. This comprehensive approach translates complex psychosocial and demographic data into actionable spatial intelligence for targeted public health interventions.

3.3 Data Collection

Data were collected using the TiS-MSU platform, which included various modules for health assessments. The key variables were defined as follows (see Figure 2). The "Senior Apps Report," produced by the Faculty of Medicine at Mahasarakham University in Thailand, provides a longitudinal analysis of loneliness metrics from a sample of 714 individuals. The data reveal a mean UCLA Loneliness Score of 18.68, with an average participant age of 54.97 years. These statistics serve as a baseline for understanding the demographic and psychosocial characteristics of the study population. The "UCLA Loneliness Score Trend" chart illustrates the changes in self-reported loneliness over 16 months, from August 2024 to November 2025. The trend line indicates considerable volatility rather than a linear progression. Initially, scores dropped to 11.96 in September 2024, then rose sharply to 28.1 by December 2024. After fluctuating in the first half of 2025, loneliness scores surged significantly in the final months. In particular, scores rose from 19.88 in October 2025 to a peak of 43 in November 2025, indicating a marked increase in participants' reported loneliness at the end of the study period. The figure (Figure 3) presents a geospatial analysis of loneliness prevalence among study participants, visualized using the "TiS-MSU" platform.

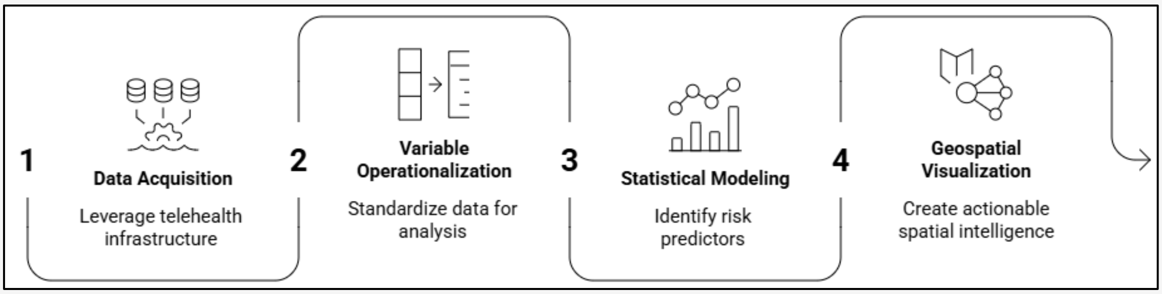

Figure 1: Four-stage research framework detailing the analytical workflow from telehealth data acquisition to geospatial visualization

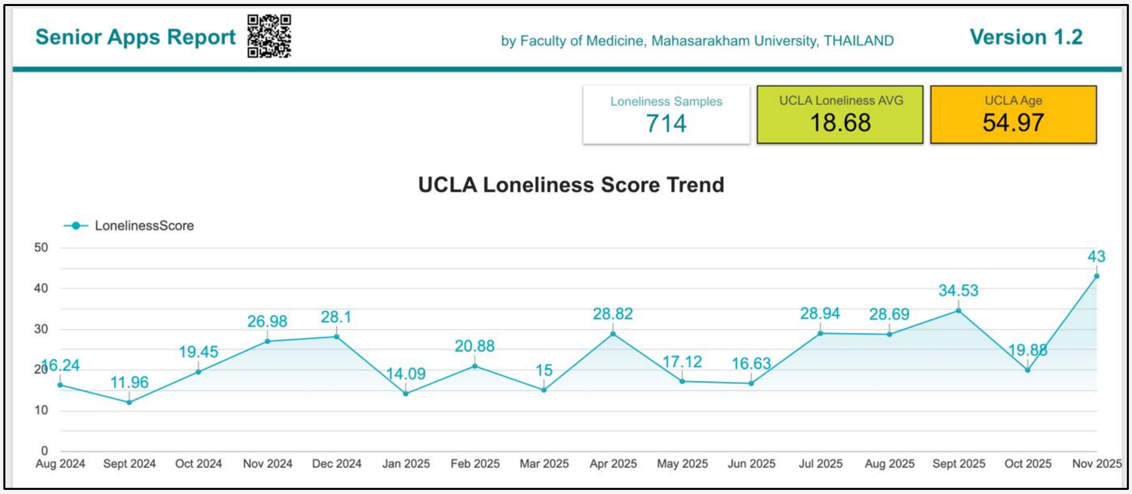

Figure 2: Longitudinal trend of mean UCLA loneliness scores (August 2024 – November 2025)

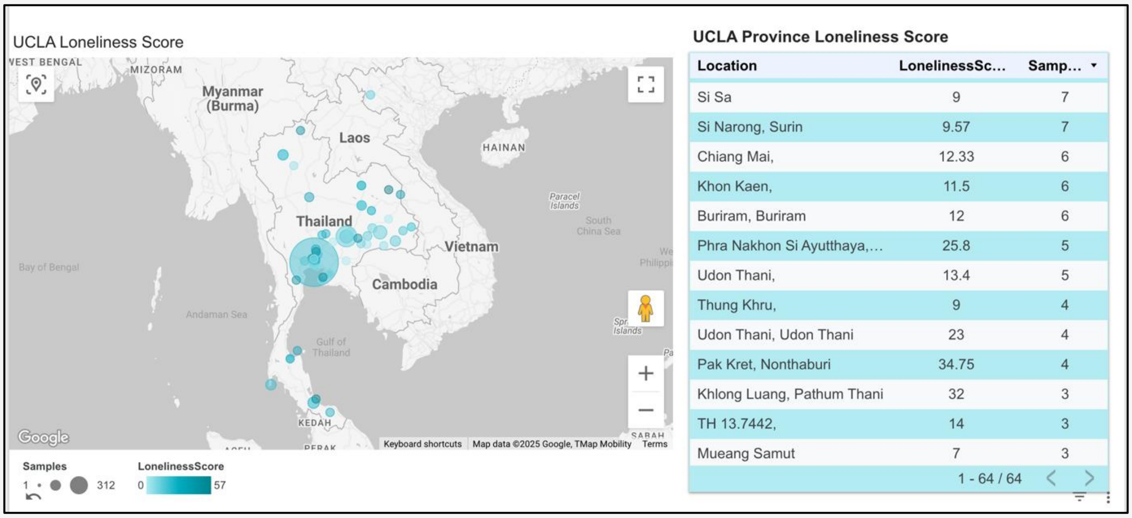

Figure 3: Geospatial distribution of UCLA loneliness scores and sample sizes across Thailand

The map on the left illustrates the nationwide distribution of data points. The diameter of each bubble marker represents the sample size (N) at that location, with the largest markers indicating up to 312 individuals. The intensity of the marker colors corresponds to the mean UCLA Loneliness Score, creating a heat map ranging from 0 (light teal) to 57 (dark teal), with higher values indicating greater feelings of loneliness. There is a notable concentration of participants in central Thailand, along with additional data points scattered throughout the northeastern, northern, and southern regions. The accompanying table provides a detailed breakdown of mean loneliness scores by location. The data reveal significant regional differences in loneliness levels. For instance, Pak Kret in Nonthaburi (Mean Score = 34.75) and Khlong Luang in Pathum Thani (Mean Score = 32) report considerably higher average loneliness scores compared to areas such as Si Sa (Mean Score = 9) and Si Narong in Surin (Mean Score = 9.57). It is important to note that the subsample sizes at these locations are relatively small, ranging from N = 3 to N = 7, which contributes to the substantial variability in mean scores across different districts. Figure 4 presents a choropleth map illustrating loneliness levels across the districts of Thailand, based on data from the UCLA Loneliness Scale. The map uses four colors to indicate varying extents of loneliness: cyan represents "Not lonely," purple signifies "Slightly lonely," pink indicates "Feeling lonely," and yellow denotes "Quite lonely." This visualization aids in identifying regional patterns and differences in emotional well-being. The map reveals that respondents classified as "Not lonely" are predominantly found in central and lower northeastern areas, such as Saraburi and Nakhon Ratchasima.

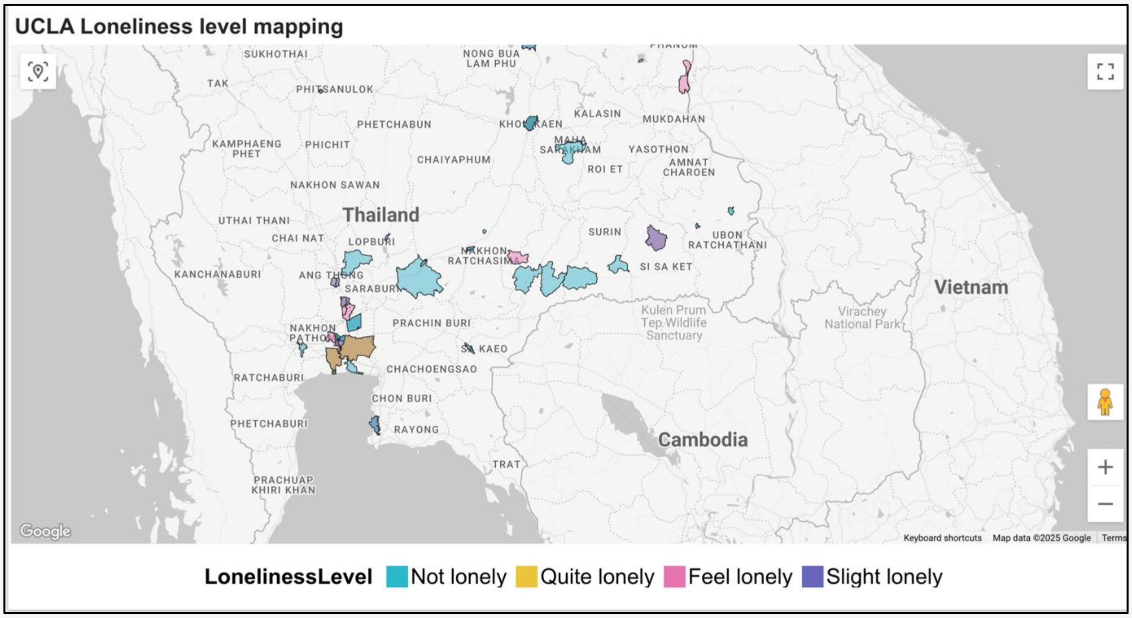

Figure 4: Geospatial mapping of categorical loneliness levels across Thai provinces

Conversely, individuals identified as "Quite lonely" are mainly located in central metropolitan districts, particularly around Nakhon Pathom and Pathum Thani. Additionally, smaller groups of "Slightly lonely" and "Feeling lonely" respondents are observed in the northeastern border provinces, including Ubon Ratchathani and Mukdahan, highlighting variations in social isolation across the country.

4. Data Analysis

4.1 Phase 1: Descriptive Analysis

4.1.1 Age distribution and loneliness level

A significant statistical pattern emerges within the "Not Lonely" classification, which represents the study's primary cohort (Frequency: 323 Females, 140 Males, 4 LGBTQ+). Individuals in the "Not Lonely" group tend to be older; specifically, the average age of males in this group is 66.25 years (SD=13.51), while females average 59.9 years (SD=18.68). These descriptive data suggest that a substantial segment of the older adult population studied maintains strong social connections, effectively reducing the likelihood of experiencing high levels of loneliness. In contrast, groups characterized by varying degrees of social isolation, specifically "Feel Lonely," "Slightly Lonely," and "Quite Lonely," exhibit lower average ages, with specific trends differing by gender (see Table 1). The "Feel Lonely" group shows mean ages of 36.21 for females and 40.47 for males. These figures are significantly lower than the averages in the "Not Lonely" group, suggesting that acute feelings of loneliness are particularly prevalent among younger adults. The "Slightly Lonely" category has the highest average age among the symptomatic groups, with females averaging 45.13 years and males 58.79 years. This implies that a mild sense of loneliness may affect a distinct demographic subset compared to the "Feel Lonely" group, with the male mean age of 58.79 closely approximating the average found in the "Not Lonely" cohort.

4.1.2 Gender differences in age and loneliness

Across all four levels of loneliness, the average age of males (40.47, 58.79, 32.61, 66.25) is consistently higher than that of females (36.21, 45.13, 30.6, 59.9) within each category. For example, among those who feel lonely, the average age of males is approximately 4 years older than that of females (40.47 vs. 36.21). The largest age difference is observed in the "Slightly Lonely" category, where the average age for males is 58.79 and for females is 45.13. This indicates a substantial age gap between genders reporting this level of loneliness.

4.1.3 Insights from LGBTQ+ cohorts

Data related to the LGBTQ+ community should be interpreted with caution due to extremely small sample sizes, ranging from N=1 to N=4. Among those surveyed, the groups identifying as "Feel lonely" and "Slightly lonely" report the lowest mean ages, at 31 and 23, respectively, compared with their male and female counterparts. This may indicate that loneliness is more prevalent among younger individuals within this demographic. Additionally, the Standard Deviation for the LGBTQ+ group identified as "Quite lonely" is reported as NaN (Not a Number) because the sample size is N=1, making it impossible to calculate variability.

4.1.4 Variability and range

The standard deviation indicates considerable age variability across most groups, suggesting that loneliness is not confined to specific age brackets but rather spans a wide range. In the "Feel Lonely" group, there is notable age variability among both females (standard deviation: 20.35) and males (standard deviation: 17.95), emphasizing the diverse ages of individuals who experience this emotion. Additionally, the age ranges are extensive across all categories; for instance, the "Not Lonely" group includes individuals aged 14 to 94. This confirms that the population includes both young adults and the elderly. The scatter plot (Figure 5) illustrates the relationship between participant age and UCLA Loneliness Scores across 714 cases. Participants' ages range from 15 to over 90 years, while their loneliness scores vary from 0 to nearly 60. A clear negative trend is evident: younger participants, particularly those aged 18 to 30, tend to have higher loneliness scores, typically ranging from 20 to 60. In contrast, participants aged 60 and above typically report lower scores, ranging from 0 to 20. This trend supports the study's conclusion that loneliness tends to decrease with age.

Table 2 shows the correlation between age and loneliness scores, revealing a moderate negative relationship ($r = -0.48$, $p < 0.001$). This suggests that as age increases, loneliness scores tend to decrease. The p-value is significantly lower than 0.05, indicating that the result is statistically significant and unlikely to have occurred by chance. However, it is important to remember that correlation does not imply causation.

4.2 Phase 2: Bivariate Analysis (Identifying Relationships)

In Table 3, the Chi-square test examining the relationship between Gender and Loneliness Level was statistically significant ($\chi^2(6) = 28.53$, $p < .001$). The degrees of freedom (*df*) were calculated as 6 using the formula (3-1) × (4-1) = 6, based on the number of categories for both variables. The Chi-square value of 28.53 indicates substantial differences between the observed and expected counts, suggesting a strong association between Gender and Loneliness Level.

Table 1: Loneliness level by gender

LonelinessLevel	Gender	Frequency	Mean	Std. Deviation	Minimum	Maximum
Feel lonely	Female	63	36.21	20.35	14	88
	Male	36	40.47	17.95	15	74
	LGBTQ+	3	31	13.11	19	45
Slight lonely	Female	86	45.13	23.39	12	89
	Male	33	58.79	19.76	15	89
	LGBTQ+	2	23	2.83	21	25
Quite lonely	Female	5	30.6	18.7	14	60
	Male	18	32.61	20.6	15	76
	LGBTQ+	1	13	NaN	13	13
Not lonely	Female	323	59.9	18.68	14	93
	Male	140	66.25	13.51	20	94
	LGBTQ+	4	43.25	5.12	38	50

Table 2: Correlation analysis for the variables age and loneliness score

	r	*p*	95% CI
Age and Loneliness Score	-0,48	<.001	[-0,54, -0.42]

Table 3: The results of a Chi-square test between gender and loneliness level

	χ^2	*df*	*p*
Gender – Loneliness Level	28.53	6	<.001

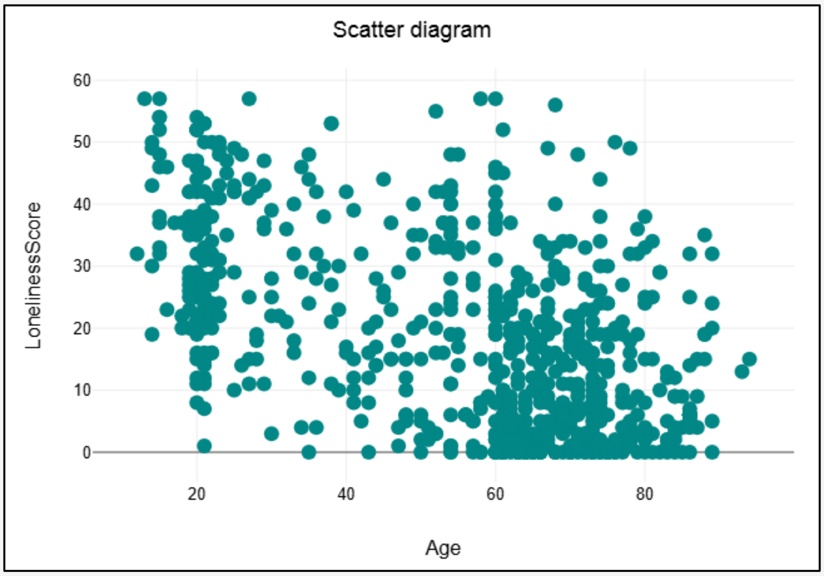

Figure 5: Scatter diagram illustrating the correlation between age and loneliness score

Table 4: A multiple linear regression model between loneliness score and age

R	R^2	Adjusted R^2	Standard error of the estimate
0.52	0.27	0.27	12.88

4.3 Phase 3: Multivariable Regression Analysis (Identifying Risk)

A multiple linear regression model is suitable for a continuous dependent variable, such as the UCLA Loneliness Scale score. In this context, the loneliness score is the dependent variable, while the independent variables are gender, age, marital status, work status, and living arrangement.

4.3.1 Loneliness score and age

The regression model presented in Table 4 indicates that 'Age' accounts for 26.85% of the variance in 'LonelinessScore'. This finding has been confirmed as significant by ANOVA, with $F = 261.32$, $p < .001$, and $R^2 = 0.27$. The correlation coefficient ($R = 0.52$) indicates a strong positive relationship between the observed and predicted scores. Therefore, the model explains approximately 26.85% of the variation in the LonelinessScore. Additionally, the Adjusted R-squared value accounts for the number of variables and the sample size, providing a more accurate measure when multiple predictors are involved. In this case, it indicates that roughly 26.75% of the variance in the dependent variable is explained after adjustment. A linear regression analysis (see Table 5) indicated that age can predict loneliness using the equation:

$$\text{LonelinessScore} = 38.76 - 0.37 \times \text{Age}.$$

This indicates that each additional year of age is related to a 0.37-point decrease in loneliness.

4.3.2 Loneliness score and gender

A multiple linear regression analysis (see Table 6) indicated that, using females as the reference group, males are expected to have a loneliness score 2.57 points higher. In comparison, LGBTQ+ individuals are expected to have a score 13.12 points higher. The model's intercept is 17.68. A multiple linear regression model (see Table 7) was used to analyze the relationship between gender identity and loneliness. The baseline predicted loneliness score for males was 20.26. Identifying as female was associated with a 2.57-unit reduction in the predicted loneliness score. In contrast, identifying as LGBTQ+ resulted in an increase in the loneliness score by 10.54 units when compared to males.

4.3.3 Loneliness score and marital status

A multiple linear regression analysis (as shown in Table 8) was conducted to evaluate the impact of marital status on loneliness. The model's intercept was 23.27, which represents the baseline Loneliness Score. Being married emerged as the strongest protective factor, reducing loneliness by 9.39 units (β = -9.39). Conversely, widowhood also contributed to a decrease in loneliness, reducing the score by 8.84 units. On the other hand, being single was associated with a 5.28-unit increase in the Loneliness Score compared to the reference group.

4.3.4 Loneliness score and work status

Multiple linear regression analysis (see Table 9) indicated a significant association between work status and feelings of loneliness. The baseline loneliness score was 22.28. Individuals categorized as "Students," "Employees," and "Experts" reported higher levels of loneliness, whereas those identified as "Laborers," "Traders," "Not working yet," "Retired," and "Managers" experienced lower levels. This suggests that certain occupations may help reduce the risk of loneliness.

Table 5: The results for each independent variable in the model

Model	Unstandard. Coef. β	Standard. Coef. β	Std. Error	t	p	95% CI for β lower bound	95% CI for β upper bound
Constant	38.76		1.33	29.09	<.001	36.15	41.38
Age	-0.37	-0.52	0.02	-16.17	<.001	-0.41	-0.32

Table 6: The results for gender (female) and loneliness score in the model

Model	Unstandard. Coef. β	Standard. Coef. β	Std. Error	t	p	95% CI for β lower bound	95% CI for β upper bound
Constant	17.68		0.68	25.82	<.001	16.34	19.03
Male	2.57	0.08	1.21	2.13	.033	0.21	4.94
LGBTQ+	13.12	0.10	4.78	2.74	.006	3.74	22.50

Table 7: The results for Gender (Male) and loneliness score in the model

Model	Unstandard. Coef. β	Standard. Coef. β	Std. Error	t	p	95% CI for β lower bound	95% CI for β upper bound
Constant	20.26		0.99	20.40	<.001	18.31	22.20
Female	-2.57	-0.08	1.21	-2.13	0.033	-4.94	-0.21
LGBTQ+	10.54	0.08	4.83	2.18	0.029	1.06	20.03

Table 8: The results for marriage status and loneliness score in the model

Model	Unstandard. Coef. β	Standard. Coef. β	Std. Error	t	p	95% CI for β lower bound	95% CI for β upper bound
Constant	23.27		2.89	8.06	<.001	17.60	28.94
Married	-9.39	-0.31	2.99	-3.14	.002	-15.26	-3.52
Single	5.28	0.16	3.03	1.74	.082	-0.67	11.24
Widowed	-8,84	-0.25	3.07	-2.88	.004	-14.86	-2.82

Table 9: Multiple linear regression analysis predicting loneliness score by work status

Model	Unstandard. Coef. *β*	Standard. Coef. *β*	Std. Error	*t*	*p*	95% CI for *β* lower bound	95% CI for *β* upper bound
Constant	22.28		1.76	12.63	<.001	18.82	25.74
Employee	6.62	0.09	3.12	2.12	0.034	0.49	12.75
Not working yet	-6.39	-0.20	1.97	-3.24	0.001	-10.26	-2.52
Student	8.86	0.17	2.50	3.54	<.001	3.94	13.78
Retirement	-5.54	-0.12	2.30	-2.41	.016	-10.06	-1.03
Laborer	-7.80	-0.20	2.15	-3.62	<.001	-12.03	-3.57
Trader	-7.21	-0.11	2.82	-2.55	.011	-12.75	-1.67
Manager	-3.48	-0.02	6.55	-0.53	.595	-16.35	9.38
Expert	4.84	0.07	3.06	1.59	.113	-1.15	10.84

Table 10: Multiple linear regression analysis predicting loneliness score by living arrangement

Model	Unstandard. Coef. *β*	Standard. Coef. *β*	Std. Error	*t*	*p*	95% CI for *β* lower bound	95% CI for *β* upper bound
Constant	23.49		1.33	17.66	<.001	20.88	26.10
Stay with family	-6.78	-0.20	1.48	-4.59	<.001	-9.69	-3.88
Live with a partner	-2.71	-0.04	2.79	-0.97	.33	-8.18	2.76
Stay with friends	3.73	0.05	2.92	1.28	.202	-2.00	9.46
Living in a nursing home	14.26	0.07	7.46	1.91	.057	-0.40	28.91
A group home	-2.74	-0.01	7.46	-0.37	.714	-17.40	11.91

4.3.5 Loneliness score and living arrangement

Table 10 presents the results of a multiple regression analysis examining the relationship between living arrangements and loneliness, using "Living alone" as the reference category. The constant (23.49; $p < .001$) indicates the baseline level of loneliness. The analysis shows that "Staying with family" has a significant protective effect against loneliness, with a coefficient (β) of -6.78 and a standardized beta (β) of -0.20 ($p < .001$). On the other hand, "Living in a nursing home" tends to increase loneliness, reflected by a coefficient of 14.26 and a beta of 0.07 ($p = .057$), although this effect is not statistically significant. Living with a partner, with friends, or in group homes was not significantly associated with loneliness.

5. Results and Discussion

5.1 Results

5.1.1 Demographic characteristics and prevalence of loneliness

The study included a cohort of 714 participants, with a mean age of 70.0 years (SD = 8.77). The demographic breakdown showed that the sample was predominantly female (66.81%), followed by males (31.79%) and LGBTQ+ individuals (1.40%). Descriptive analysis indicated that most participants (65.41%) identified as "Not lonely." Loneliness prevalence was highest among LGBTQ+ individuals, followed by males, while females reported the lowest levels of perceived isolation. Correlation analysis revealed a moderate, statistically significant negative relationship between age and loneliness scores ($r(712) = -0.48$, $p < .001$), suggesting that loneliness tends to decrease with age. This trend was further evident in the mean ages across the different loneliness categories: the "Not lonely" group had the highest mean age (61.66 years), while the "Quite lonely" group had the lowest (31.38 years). Additionally, loneliness scores significantly differed by work status ($F = 13.32$, $p < .001$) and gender ($F = 5.60$, $p = .004$).

5.1.2 Multivariable regression analysis: predictors of loneliness

A hierarchical multiple linear regression model identified age as the primary predictor of loneliness, accounting for 27% of the total variance ($R^2 = 0.27$, $p < .001$). The analysis confirmed a significant inverse relationship: each increase in age was associated with a reduction in loneliness scores ($\beta = -0.52$, $\beta = -0.37$). Gender and professional status were also important predictors. Compared to females, males ($\beta = 2.57$) and LGBTQ+ individuals ($\beta = 13.12$) reported significantly higher levels of loneliness. Regarding occupation, students (B = 8.86) and employees (B = 6.62) experienced greater loneliness than other groups. Protective social factors included being married ($\beta = -9.39$) or widowed ($\beta = -8.84$), both of which were significantly associated with lower loneliness levels. Additionally, living with family members was a protective factor ($\beta = -6.78$), while residing in a nursing home was linked to increased loneliness. However, this effect did not reach statistical significance ($\beta = 14.26$, $p = .057$).

5.2 Discussion

This investigation marks the first nationwide analysis in Thailand to evaluate predictors of loneliness using the "TiS-MSU" telehealth platform. The successful execution of this study demonstrates the effectiveness of integrating digital health technologies with the extensive network of Village Health Volunteers (VHVs) for scalable public health surveillance. The findings challenge traditional beliefs about social isolation by revealing a strong inverse correlation between age and loneliness ($r = -0.48$). Contrary to the common assumption that elderly populations experience the most isolation, the "Quite lonely" group was significantly younger than the "Not lonely" group. Age alone accounted for 27% of the variance in loneliness, suggesting that younger cohorts, particularly Gen Z and working-age adults, may be more vulnerable to feelings of disconnection due to digital isolation or economic stressors. The understanding of loneliness was further refined by considering work and marital status. While Western literature often depicts widowhood as a major contributor to isolation, this study found that widowed participants in Thailand reported lower levels of loneliness. This is likely due to the robust support provided by Thai extended family systems, where widowed elders often receive help from relatives. Living arrangements also proved to be an important social factor; cohabiting with family members was strongly associated with lower levels of loneliness. Although nursing home residents tended to experience increased loneliness, the data showed no statistically significant difference ($p = .057$), highlighting the significant advantages of direct family presence.

Moreover, recent applications of machine learning in Thai communities have shown that predicting loneliness requires understanding the complex interactions among functional and psychological factors, as well as basic demographic information. This suggests that future predictive models should incorporate these dimensions for a more comprehensive assessment [33].

Geospatial health research in Thailand enhances our findings and provides context for our spatial approach. For example, Geographic Information Systems (GIS) was utilized to identify physical health disparities among the elderly, revealing gaps in caregiver coverage and prioritizing interventions for chronic diseases [37]. This approach is consistent with our use of spatial intelligence in developing targeted public health strategies. However, while the study focused on vulnerabilities associated with aging, our study demonstrates that psychosocial risks, such as loneliness, do not follow the same age pattern. The strong extended family systems in Thailand offer protection for older adults against emotional isolation, which inadvertently shifts the burden of loneliness onto younger, working-age individuals. These insights highlight the necessity of a comprehensive public health strategy that employs geospatial tools to address both the physical health decline among the elderly and the psychosocial isolation among younger populations.

Similarly, GIS was used to analyze and model Melioidosis prevention in Si Sa Ket Province [38]. Their study effectively identified high-risk environmental zones and vulnerable populations, particularly noting a high prevalence of the disease among working-age males in agriculture. Mapping these risk areas informed targeted disease surveillance to reduce exposure to contaminated environments. In contrast, our research applies a comparable spatial framework to investigate a non-communicable psychosocial condition. Both studies identify working-age males as highly vulnerable; however, while [38] attribute this vulnerability to physical occupational risks, our analysis indicates

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that younger adults and working-age males face increased levels of loneliness due to social and economic stressors.

This integration suggests that geospatial health surveillance in Thailand needs to address two crucial areas: infectious disease hotspots and regions with significant psychosocial vulnerability. As a result, public health interventions should expand their focus beyond the needs of the elderly alone. They must also incorporate comprehensive support systems for younger working populations and students who are at high risk of acute loneliness. These strategies must promote the overall well-being of the entire population.

6. Summary and conclusion

6.1 Nationwide Evidence of Loneliness Risk

This research presents the first comprehensive evidence from Thailand identifying the main predictors of loneliness among adults. By leveraging the "TiS-MSU" telehealth platform and an extensive network of Village Health Volunteers (VHVs), the study established a scalable model for public health surveillance and data collection across diverse demographics. Recent public health preparedness frameworks demonstrate that geographic information systems (GIS) and spatial analytics are essential for tracking health threats and optimizing resource distribution at the community level [39].

6.2 Demographic Vulnerabilities

Contrary to traditional beliefs that view the elderly as the most vulnerable demographic, this study reveals that younger individuals, particularly students and workers, report higher levels of loneliness. A multiple linear regression analysis indicates that age is the strongest predictor of loneliness, demonstrating a significant inverse relationship: feelings of isolation tend to decrease as age increases ($R^2 = 0.27$, $p < .001$). Additionally, individuals within the LGBTQ+ community and males reported significantly higher loneliness scores compared to their female counterparts.

6.3 Social and Environmental Protectors

The findings indicate that socio-environmental factors are stronger predictors of emotional well-being than individual behaviors as follows:

- *Marital status*: Being married ($\beta = -9.39$) or widowed ($\beta = -8.84$) is a significant protective factor against loneliness.
- *Living arrangement*: Living with family significantly reduces feelings of isolation ($\beta = -6.78$). In contrast, residing in a nursing home tends to increase the risk of loneliness, underscoring the critical importance of maintaining family ties in Thai society.
- The findings indicate that socio-environmental factors are more powerful predictors of emotional well-being than individual behaviors.

6.4 Public Health Recommendations

Future public health strategies in Thailand should expand their focus beyond just the elderly population to include targeted interventions for younger working-age groups. The following recommendations are proposed:

- *Prioritize high-risk groups*: Intervention programs should specifically address the needs of students, employees, and LGBTQ+ individuals.
- *Strengthen social networks*: Support systems should enhance family-based care and promote social roles that facilitate meaningful interpersonal connections.
- *Address digital and economic factors*: Policies must consider modern risk factors such as digital disconnection and economic stress, which significantly affect the mental health of younger Thai adults.

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