Identifying Influential Predictors of Loneliness in a Thai Community: A Cross-Sectional Machine Learning Analysis

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Abstract

This research addresses the increasing public health concern of loneliness within the Thai community by developing and validating a Machine Learning (ML) model for risk detection. The objective is to use ML to identify the most influential psychological, physical, and socioeconomic factors contributing to loneliness, providing insights that extend beyond standard self-assessments. A cross-sectional, multi-platform data collection approach was utilized, employing the LINE application (the "Senior Thailand" Official Account) and the "senior.in.th" website to gather comprehensive information from 616 adults across various provinces in Thailand. The methodology included all 12 factors for predictive modeling, encompassing sociodemographic traits, lifestyle habits (e.g., exercise and Activities of Daily Living), physiological metrics (e.g., BMI and blood pressure), and detailed mental health assessments (e.g., UCLA Loneliness Scale and Depression/Anxiety scales). Four algorithms Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine (SVM) were trained and evaluated. The Logistic Regression model showed the best performance, achieving a Classification Accuracy (CA) of 0.707 and the highest Area Under the Curve (AUC) of 0.697. However, the low Matthews Correlation Coefficient (MCC) of 0.253 and the moderate AUC suggest that, while the model has utility, the complexity of loneliness requires further hyperparameter tuning and model optimization. Overall, this study successfully validates a multi-factor ML model for loneliness prediction, revealing that the most significant predictors are psychological and functional barriers (such as depression and Activities of Daily Living). This outcome highlights the potential for ML to inform targeted public health strategies and promote social well-being by prioritizing interventions based on data-driven insights.

Keywords: Cross-sectional Study, Loneliness Scale, Machine Learning, Predictive Modeling, Thai Community

1. Introduction

Loneliness is a significant and distressing emotional state characterized by a subjective feeling of social isolation and a profound sense of disconnection from others. In Thailand, this issue is becoming increasingly prevalent due to rapid urbanization, shifting social and economic structures, and ongoing cultural transformations. It disproportionately affects older adults and individuals in rural areas [1]. The consequences of loneliness can be considerable, leading to an increased risk of mental health issues such as depression and anxiety, as well as chronic diseases, cognitive decline, and even premature mortality. Physical limitations that restrict social participation, life transitions such as retirement, and the loss of a spouse or friends can all increase the risk of loneliness among older adults.

Rapid urbanization significantly impacts social networks in Thailand. Traditionally, rural communities relied heavily on strong connections with extended family and neighbors for both emotional and practical support. However, moving to urban areas often disrupts these relationships, leading to culture shock, difficulties in adapting, and feelings of isolation. The migration of young adults to cities for education and employment also reduces intergenerational contact, thereby increasing isolation among older adults who depend on familial care. Additionally, a considerable stigma surrounding mental health in Thailand serves as a cultural barrier, often preventing individuals from seeking the necessary help and support. While technology offers new ways to connect, overreliance on social media can ironically heighten feelings of loneliness and social comparison.

Despite existing research into various aspects of loneliness, significant gaps remain in our understanding of its dynamic nature and the predictive accuracy of risk across different cultural contexts. Many current studies have limitations regarding the generalizability of their findings, particularly when attempting to apply insights from depression research to the complex concept of loneliness. Moreover, reliance on self-reported data may introduce biases, while the lack of longitudinal data limits our ability to understand how loneliness develops over time. It is also crucial to explore the feasibility of integrating AI-driven tools into existing healthcare systems for practical application. This study aims to address existing research gaps by employing a multi-platform data collection approach that utilizes both the LINE application and a dedicated website, along with advanced machine learning techniques, to investigate and predict the risk of loneliness among Thai adults. The findings aim to inform public health policies and interventions, ultimately reducing loneliness and promoting social well-being nationwide. The primary aims of this study are:

- To construct an AI-driven model capable of predicting the risk of loneliness among a diverse Thai population by evaluating various demographic, lifestyle, and mental health factors.
- To assess the effectiveness of using digital platforms, specifically the LINE application and dedicated web tools, for collecting continuous, cost-effective public health data in the Thai cultural context.
- To utilize ML-derived insights to suggest data-driven public health strategies and social support programs tailored to high-risk demographic groups.

2. Literature Review

2.1 Prevalence of Loneliness in Thailand

Research conducted in Thailand has identified loneliness as a significant public health issue that affects various demographic groups, mainly due to changing sociocultural structures. Among vulnerable populations, studies show that over 40% of sexual and gender minority (SGM) individuals experience clinically significant loneliness [2] This feeling often results from minority-specific stressors and systemic discrimination, with loneliness acting as a key mediator between social stress and the development of depressive symptoms. The individual and social factors contributing to loneliness also extend to specialized care settings. For example, clinical studies of residents in long-term care facilities demonstrate a strong correlation between insecure attachment styles and higher levels of reported loneliness. However, research suggests that these psychological vulnerabilities can be mitigated; practices such as meditation have been found to lessen the adverse effects of insecure attachments, providing a promising psychological intervention to alleviate social disconnection.

Beyond clinical populations, cultural and systemic factors significantly shape family caregivers' experiences [3]. Research indicates that caregivers' well-being depends heavily on the strength of their social support networks and the specific cultural expectations within Thai family structures. These findings collectively underscore that loneliness in Thailand is not merely a result of individual isolation but rather a complex phenomenon shaped by the interplay of social, cultural, and psychological factors. Addressing this requires comprehensive predictive modeling to support effective public health interventions.

2.2 Influencing Factors and Loneliness Mechanisms

Loneliness is often associated with various demographic factors; however, these associations can be attenuated when broader social and psychological factors are incorporated into predictive models. Physical health issues, mental health disorders, and certain psychological traits such as neuroticism and extroversion show strong correlations with feelings of loneliness. In the current research context, the quality and quantity of social interactions are the primary determinants of isolation [4]. Factors including marital status, living arrangements, and the structural characteristics of an individual's social network consistently predict the depth of reported loneliness. The risk of experiencing loneliness varies significantly across different life stages and socioeconomic levels. Older adults are at a heightened risk due to specific life transitions, such as mandatory retirement, the loss of spouses or peers, and general physical decline. Gender dynamics also contribute, with evidence suggesting that women may be slightly more vulnerable to loneliness than men. Unmarried individuals, such as those who are

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widowed, divorced, or separated, are considered a high-risk demographic. Moreover, structural inequalities like limited educational attainment and lower income levels are associated with greater vulnerability, while living alone in rural areas with sparse social support further worsens feelings of isolation [5] [6] [7] and [8]

A lack of meaningful social connections and mobility is another critical risk factor. Physical limitations that prevent individuals from engaging with their communities can hinder social interaction. Although digital platforms offer alternative means of connection, excessive reliance on social media can ironically decrease face-to-face engagement, thereby increasing isolation [9] Mental health issues, particularly depression and anxiety, significantly contribute to patterns of withdrawal. These conditions often create a vicious cycle, where poor mental health reduces social engagement, which in turn reinforces long-term loneliness [10].

In Thailand, these factors are exacerbated by rapid societal changes. Urbanization has disrupted traditional family and community support systems, especially as young adults move to cities, leaving older populations without immediate intergenerational care. This transformation, along with the cultural stigma surrounding seeking mental health support, leads to a cycle in which feelings of isolation remain unaddressed. Therefore, effective public health interventions in the Thai context must adopt a multifaceted approach that accounts for the complex interplay among sociodemographic changes, digital lifestyle shifts, and psychological comorbidities to address this emerging social crisis [2] [5] and [11].

2.3 Loneliness Assessment Tools

Evaluating loneliness throughout the lifespan requires the use of psychometrically robust instruments. Confirmatory factor analysis (CFA) and local structural equation modeling (LSEM) were employed to investigate the measurement invariance of the UCLA Loneliness Scale in individuals aged 18 to 99 [12].Their findings indicated a lack of age invariance in the scale, suggesting that perceptions or reports of loneliness may differ across age groups. As a result, the researchers advise against making direct comparisons between age groups without first establishing measurement invariance for the specific study population. Eight widely used loneliness scales were examined by a meta-nalysis technique [13].While many of these scales demonstrated strong psychometric foundations, the researchers identified significant limitations regarding test-retest reliability and measurement invariance. This study highlights that some instruments include items that may not accurately capture the subjective experience of loneliness, underscoring the need for multidimensional assessment strategies to better understand the complexity of social isolation.

In a comparative analysis of loneliness metrics in adulthood, the Rasch-Type Loneliness Scale, the UCLA Loneliness Scale, and three single-item measures were evaluated. Their results showed high correlations among these tools, suggesting that even single-item assessments can be valid and reliable for measuring loneliness in adult populations [14]. Further regional and clinical validations have been conducted, the 20-item, 8-item, and 3-item Chinese versions of the UCLA Loneliness Scale in Taiwan were examined [15]. This study involved 267 participants, most of whom were diagnosed with schizophrenia (89.0%) or schizoaffective disorder (11.0%). The research confirmed that all three versions maintained acceptable psychometric properties for assessing loneliness within this clinical demographic. The cohort had a mean age of 45.88 years and a mean illness duration of 18.94 years, exhibiting mild-to-moderate symptoms, thereby reinforcing the scale's utility in specialized healthcare settings.

2.4 Comparative Methodological Frameworks and ML Context

Longitudinal cohort studies are valuable for tracking individuals over time to establish temporal relationships between exposures and outcomes [2], [16] However, they often require substantial resources and are susceptible to participant attrition. Previous research utilizing cohort designs has effectively identified loneliness as a crucial precursor to adverse health outcomes. For example, it revealed through a 12-year follow-up that loneliness significantly increases the likelihood of developing depressive symptoms in older adults [6]. Additionally, the English Longitudinal Study of Ageing (ELSA) employed a prospective cohort approach to explore how loneliness mediates the relationship between chronic physical illness and depression [7].

In light of recent global stressors, participants were tracked across three waves during the COVID-19 pandemic, further confirms that increased loneliness is strongly linked to higher rates of depression and substance use [8]. These longitudinal findings highlight the dynamic and predictive role of loneliness as a public health metric. In contrast, the current research employs a cross-sectional design, collecting multi-platform data from 616 Thai adults at a single point in time. This approach prioritizes breadth and diverse representation across various provinces. While it does not track temporal changes,

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it provides a crucial snapshot of Thailand's current sociodemographic and mental health landscape. This snapshot serves as a baseline for developing predictive machine learning models that identify individuals at high risk of loneliness based on immediate lifestyle and health indicators. Predictive modeling in public health often utilizes various study designs to evaluate risk. This research, however, adopts a cross-sectional approach to assess loneliness among 616 Thai adults. While traditional epidemiological designs, such as cohort or case-control studies, provide valuable longitudinal insights, they are often resource-intensive. In contrast, this study employs a cross-sectional, multi-platform framework using tools such as the LINE application and the senior.in.th website. This approach enables the rapid collection of diverse sociodemographic and lifestyle data, which is crucial for training machine learning (ML) algorithms to identify subtle patterns specific to cultural contexts, such as unique loneliness risks within the Thai community.

The integration of ML into health assessments represents a significant shift in understanding human behavior. Recent studies have demonstrated the effectiveness of these methods in predicting life satisfaction in extensive national surveys, achieving accuracy rates of up to 93.8% [17]. By employing techniques such as Logistic Regression and Random Forests, this study aims to clarify risk factors beyond simple demographic correlations. The focus shifts from mere classification to identifying the most influential predictors of loneliness, including Activities of Daily Living (ADL), Body Mass Index (BMI), and blood pressure factors that may not be adequately captured through standardized questionnaires alone. This data-driven approach lays the foundation for informing future public health interventions and policy development in Thailand.

2.5 Machine Learning in Loneliness Prediction

Recent developments in computational psychiatry have shown that machine learning (ML) is an effective tool for identifying predictive patterns of social isolation among diverse populations. Research that utilizes ML to study individuals with mental illnesses, such as schizophrenia and bipolar disorder, indicates that social anhedonia, the reduced ability to experience pleasure from social interactions, serves as a universal predictor of loneliness [18]. While the physical and cognitive health risks are well documented, specific factors, such as nonsocial cognition, appear to contribute to social disconnection in clinical groups uniquely. These findings suggest that ML models can capture complex, multifaceted drivers of loneliness that traditional self-assessments may overlook.

The application of ML extends beyond clinical groups to broader public health contexts, including pediatric and student populations. Studies focused on schoolchildren have demonstrated that ML can effectively classify the risk of loneliness, thereby facilitating the establishment of early support systems [19]. Similarly, international student surveys have successfully employed Random Forest models to predict mental health outcomes with up to 80% accuracy, identifying loneliness, along with financial and academic stress, as primary determinants of psychological well-being [20]. These studies highlight the prevalence of loneliness as a significant public health issue that disproportionately affects marginalized or transitioning demographics.

In geriatric care, ML models trained on longitudinal surveys, such as the Chinese Longitudinal Healthy Longevity Survey (CLHLS), have achieved approximately 78.5% accuracy in identifying individuals at risk of loneliness [21]. These predictive tools provide a data-driven foundation for community-based interventions that enhance the quality of life for older adults. In Thailand, this study builds on established modeling techniques by using a cross-sectional, multi-platform dataset to capture cultural nuances unique to the Thai community, thereby advancing the development of more localized public health intervention strategies.

2.6 Influencing Factors for Loneliness Prediction

The variables selected for predicting loneliness were based on established public health literature that identifies key risk factors affecting aging and transitioning populations. A total of twelve specific predictors were used to train the machine learning models, organized into three main categories. The first category comprises sociodemographic factors, including age, gender, marital status, employment status, and monthly income. The second category includes lifestyle and physiological factors, assessing physical determinants such as Body Mass Index (BMI), systolic and diastolic blood pressure, and self-reported exercise habits. The third category encompasses functional and mental health factors, measured using various instruments. These include the Activities of Daily Living (ADL) scale to evaluate functional independence, the Thai Activities Index (TAI) for mobility assessment, and psychological screening tools such as the Thai Anxiety Inventory, the 9Q/2Q depression scales, and the UCLA Loneliness Scale. Incorporating this broad spectrum of multifaceted variables is critical for the predictive model's performance. As confirmed by the initial regression analysis, simple demographic predictors, specifically age and gender, account for only a minimal amount of variance in loneliness levels among Thai adults. Therefore, a diverse range of predictive factors is essential to capture the cultural and social complexities of loneliness in Thailand.

2.6.1 UCLA loneliness scale

The primary outcome of this study was assessed using the UCLA Loneliness Scale (Version 3), a validated self-report tool designed to measure feelings of social isolation and the perceived gap between an individual's desired and actual social relationships. This scale focuses on key aspects of social disconnection, including a lack of companionship, feelings of being "left out," and overall isolation. For this research, the 20-item format was chosen due to its strong psychometric properties and high internal consistency in evaluating general adult populations. Participants responded to the items using a 4-point Likert-type scale, where 1 = "never" and 4 = "always." The application calculates a cumulative score to determine the severity of social disconnection. In accordance with established clinical and research norms, participants are categorized into four distinct degrees of loneliness rather than "risk" levels. A score of 24 is the critical cutoff point for distinguishing between non-lonely individuals and those experiencing social isolation. The specific classifications are as shown in Table 1. Using these standard thresholds enables precise identification of individuals at high risk within the community, facilitating targeted mental health interventions and support strategies.

2.6.2 Body Mass Index (BMI)

Body Mass Index (BMI) is a standardized measure used to assess body composition and identify potential health risks associated with underweight, overweight, and obesity in the Thai population. In this study, BMI is calculated from participants' self-reported height and weight, collected via the integrated "senior.in.th" website and the "Senior Thailand" LINE application. The inclusion of BMI as a predictor is supported by prior epidemiological research that highlights a bidirectional relationship between body composition and social isolation. A higher BMI is often linked to reduced mobility and an increased prevalence of chronic health conditions, factors that can limit social participation and may contribute to feelings of loneliness. On the other hand, individuals who are socially disconnected might adopt sedentary behaviors or have poor dietary habits, which can further influence their BMI. By incorporating BMI as one of the 12 primary factors in this study, we aim to improve the accuracy of machine learning classifiers in identifying subtle lifestyle predictors of loneliness among the target population [9] [22] [23] [24] and [25].

2.6.3 Blood Pressure

The assessment of cardiovascular health is integrated into this framework through blood pressure measurements, specifically systolic (SYS) and diastolic (DIA) readings. Systolic pressure measures the force of blood against the arterial walls during heart contraction, while diastolic pressure indicates the resting pressure in the arteries. The multi-platform approach, utilizing the LINE OA application, allows users to log and monitor these metrics. Users receive immediate feedback through visual scales that categorize the readings into established stages, such as "Normal," "Prehypertension," and "Stage 1 Hypertension." This systematic categorization serves two purposes: it enhances individual health literacy and populates a database that is essential for investigating physiological predictors of psychological states [26]. Integrating blood pressure data into this loneliness study is scientifically justified due to the bidirectional relationship between physical and mental health. Epidemiological evidence shows that clinical loneliness is a significant risk factor for chronic cardiovascular conditions. Conversely, research indicates that individuals with poorer physical health, such as those managing hypertension, often experience limited social mobility, which can further increase their feelings of loneliness. By including these physiological indicators, the model can identify non-demographic predictors of social isolation.

Table 1: UCLA loneliness score range

UCLA Loneliness Score Range	Degree of Loneliness	Intervention Priority
< 24	Not Lonely (Low Degree)	Baseline / Monitoring
24 – 34	Slight Degree of Loneliness	Early Support
35 – 49	Moderate Degree of Loneliness	Targeted Intervention
> 50	High Degree of Loneliness	Critical Support

2.6.4 Activities of Daily Living (ADLs)

Activities of Daily Living (ADLs) were assessed using standardized instruments aimed at measuring an individual's ability to perform essential self-care tasks independently. In this study, the ADL scale is a crucial indicator of both physical and functional health, covering key activities such as mobility, personal hygiene, and self-feeding. The use of functional metrics is important because research shows that a decline in ADL proficiency often precedes limited social participation. When a person's independence in daily activities is compromised, it can lead to decreased community engagement, which in turn can result in feelings of social isolation and loneliness [27] and [28] The data collected from these assessments enable the systematic classification of individuals based on their functional performance, helping to identify those who may be vulnerable and in need of specific support or intervention. Additionally, by quantifying self-care capabilities, the model can highlight functional barriers that may predict loneliness among the Thai population. This information provides healthcare administrators with a data-driven foundation for resource allocation, ultimately guiding the development of community programs that promote healthy aging and support ongoing functional independence.

2.6.5 TAI (Thai Activities Index) Scale

The Thai Activities Index (TAI) is a comprehensive assessment tool initially validated for evaluating the health and functional status of the elderly population in Thailand. It measures an individual's ability to perform essential daily tasks, including mobility, feeding, toileting, dressing, bathing, and cognitive function. In the context of the current study, which spans a broader age range from 18 to 99 years, the TAI remains a valuable predictor of functional independence and a means of preventing social isolation. Functional impairment, as indicated by low TAI scores, contributes to loneliness, as reduced mobility and physical dependence significantly limit an individual's ability to maintain social connections and engage with the community. By quantifying independence, the TAI provides caregivers and healthcare professionals with objective data to identify individuals experiencing functional decline. This data-driven insight enables the design of timely interventions aimed at preventing the transition from physical dependency to chronic loneliness. Similar to the Activities of Daily Living (ADL) scale, the TAI serves as a key sociodemographic predictor in the machine-learning framework, ensuring that the model accounts for the cultural and functional nuances of Thai health contexts.

2.6.6 Exercise Scale

The study utilized a dedicated exercise scale within the digital platform to systematically measure participants' physical activity levels and habits. This tool collected data on the frequency, duration, and intensity of activities such as walking, cycling, swimming, dancing, and weightlifting [29]. The rationale for including this factor stems from the established bidirectional relationship between physical health indicators and loneliness. A sedentary lifestyle and insufficient physical activity are consistently linked to increased feelings of isolation and disconnection. On the other hand, regular physical activity promotes overall health and creates opportunities for social engagement, thereby reducing the risk of loneliness. The collected data offer valuable insights for designing interventions that encourage physical activity to enhance both physical and social well-being within the community.

2.6.7 Depression, 9Q, and 2Q Scales

The inclusion of depression scales is a crucial aspect of the research framework, as depressive symptoms are a significant public health concern closely linked to social isolation. Current literature highlights a strong bidirectional relationship: chronic loneliness often worsens depressive symptoms, while the social withdrawal associated with depression can intensify feelings of isolation, creating a self-reinforcing cycle [9] [18] [30] and [31] In this study, mental health status was assessed using the Thai 9-Question (9Q) and 2-Question (2Q) depression screening tools. These scales were selected for their brevity and established validity in the Thai clinical context, providing a comprehensive assessment of participants' well-being beyond basic demographic characteristics. By quantifying the presence and severity of depressive symptoms, the machine learning models can more accurately identify how these indicators interact with physical metrics such as BMI and blood pressure to predict an individual's overall level of loneliness, surpassing the accuracy of univariate assessments.

3. Methodology

The research framework, as shown in Figure 1, outlines a multistage approach to identifying the risk of loneliness through digital integration and data science. The process begins with the Data Collection Platform, which employs a multi-platform strategy utilizing the LINE Official Account ("Senior Thailand") and the "senior.in.th" website.

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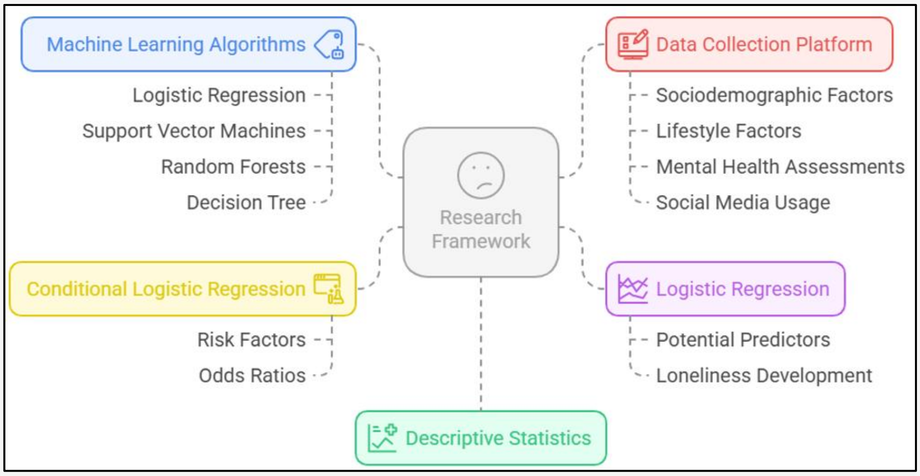

Figure 1: Research an AI modeling framework

These digital tools are used to gather a comprehensive dataset from 616 Thai adults, capturing variables across four primary domains: sociodemographic factors (e.g., age and marital status), lifestyle factors (e.g., BMI and blood pressure), mental health assessments (e.g., Depression 9Q/2Q and ADL scales), and social media usage patterns. Once the data are organized, they are analyzed to determine baseline characteristics. To enhance methodological transparency, descriptive statistics are employed to summarize the sample distribution. Although simple linear models, such as multiple linear regression, can provide initial insights into age and gender, they typically have weak explanatory power. Therefore, the framework proceeds to the machine learning algorithms phase, in which four classifiers are trained: logistic regression, support vector machines (SVMs), random forests, and decision trees.

The goal of this hierarchical methodology is twofold: to categorize respondents into validated loneliness levels (as defined by the UCLA Loneliness Scale) and to identify the predictors that most strongly contribute to social disconnection within the Thai community. This data-driven framework serves as the foundation for model evaluation, using metrics such as AUC, accuracy, and the Matthews Correlation Coefficient (MCC) to ensure the reliability of subsequent public health interventions. The primary analytical goal is to move beyond simple descriptive statistics and establish a predictive Machine Learning (ML) model using a single-point, cross-sectional dataset collected from 616 participants. The classification is informed by 12 comprehensive predictive factors, which include:

- *Sociodemographic:* Age and gender, serving as fundamental non-linear inputs for the ML models.

- *Health and Lifestyle Metrics:* These consist of Body Mass Index (BMI), blood pressure, Activities of Daily Living (ADLs), Thai Activities Index (TAI) scores, and exercise habits.

- *Mental Health Assessments:* Various psychological metrics, such as the Depression and Thai Anxiety Inventory (TAI) scales.

These variables are crucial for understanding the complex nature of loneliness. The ML algorithms are trained to identify patterns and relationships among these features, enabling accurate predictions of loneliness classifications for everyone. This approach aims to achieve the study's core predictive objective.

3.1 Influencing Factors and Measurement Scales: Sample Distribution

This study utilizes 12 distinct variables grouped into four main categories: Sociodemographic, Lifestyle, Physical Health, and Mental Health, to predict loneliness. The selection of these variables is based on extensive research linking them to social isolation and mental well-being. Participants were recruited via the "Senior Thailand" LINE application and the "senior.in.th" website, enabling them to complete health questionnaires aligned with their interests. As a result, the sample size (N) varies across individual factors. This detail is presented below to ensure methodological transparency and to facilitate accurate interpretation of the correlation results. The sample sizes for specific continuous health metrics (e.g., TAI, ADLs) exceed the total cohort of 616. This indicates that data were collected at multiple time points from users who repeatedly engaged with the specific health surveys on the platform. The research team aggregated this data for cross-sectional analysis. The smallest sample sizes were observed for socio-demographic factors (Age, Gender, Marital Status), which likely required specific user input during the platform's initial setup. This variation in sample sizes highlights the diverse nature of the multi-platform data collected.

3.1.1 Mental health and outcome factors
These scales served either as direct outcome variables or were included because of their strong reciprocal relationship with loneliness.

- *UCLA Loneliness Scale (Version 3, 20-item format):* This is the primary outcome variable that measures the perceived discrepancy between desired and actual social relationships. It directly assesses the phenomenon being investigated.

- *Thai Anxiety Inventory (TAI) Scale:* This scale measures anxiety levels, which are strongly and often bidirectionally linked to loneliness. Feelings of social isolation can exacerbate anxiety symptoms and vice versa.

- *Depression Scales (9Q/2Q):* Depression is highly correlated with loneliness and can lead to social withdrawal, further intensifying feelings of isolation. Either the 9Q or 2Q scale was employed to measure depressive symptoms; the specific version used will be clarified in the full methodology.

3.1.2 Physical health and functional status
Physical health indicators are crucial as they often mediate opportunities for social interaction and community engagement.

- *Body Mass Index (BMI):* This measure assesses body composition to evaluate general health status and the prevalence of obesity or being overweight. Loneliness is associated with increased health risks, and poor physical health (including a high BMI) can limit mobility and social engagement.

- *Blood Pressure (Systolic and Diastolic):* These are essential physiological indicators for assessing cardiovascular health. High blood pressure is regarded as a traditional cardiovascular risk factor, and loneliness is linked to a greater risk of chronic diseases and adverse health outcomes.

- *Activities of Daily Living (ADLs) Scale:* This scale measures an individual's ability to perform basic self-care tasks, indicating functional health. A decline in ADLs can physically limit social participation, which can directly increase feelings of loneliness and social isolation.

- *Thai Activities Index (TAI) Scale:* This scale assesses the health and functional abilities of Thai individuals, focusing particularly on mobility and essential self-care activities. Like ADLs, limited mobility assessed by the TAI can restrict social interactions, contributing to loneliness.

3.1.3 Sociodemographic and lifestyle factors
These factors provide baseline context regarding a participant's social environment and health behaviors.

- *Age and Gender:* These fundamental demographic variables are consistently studied as predictors of mental health outcomes. While they are often weak predictors of loneliness individually, they are crucial for segmentation and defining model cohorts.

- *Marital Status:* This is a consistently strong predictor of loneliness, as individuals who are widowed, divorced, or separated are often at a higher risk of social isolation compared to those who are married or in stable relationships.

- *Employment Status:* Economic and occupational stability can influence social networks and daily routines. Changes in employment status, or the absence of employment, can lead to financial stress and isolation.

- *Monthly Budget:* This serves as an indicator of socioeconomic status; lower income is associated with a higher risk of loneliness due to limitations in resources that affect social participation.

- *Exercise Scale:* This measures participants' physical activity levels and habits. A lack of physical activity and a sedentary lifestyle are linked to increased feelings of isolation and disconnection.

Including all 12 factors is essential to the model's objective of identifying nonlinear predictors, as basic demographic information alone has weak explanatory power ($R^2 = 0.10$).

Mental Health (e.g., Depression/Anxiety): These factors are important due to their strong reciprocal and bidirectional relationship with loneliness.

Functional Status (ADLs, TAI): These measures evaluate an individual's physical ability to participate in community activities. A decline in Activities of Daily Living (ADLs) significantly limits social engagement, thereby increasing isolation.

Physiological Health (BMI, Blood Pressure): These factors are included because health risks are bidirectionally associated with mental health; poor physical health can limit social mobility and engagement.

Socio-Demographic Factors (Age, Marital Status): Although they may be weak linear predictors, these factors are crucial for cohort segmentation. Marital status remains a significant predictor of network quality.

This comprehensive approach ensures that the machine learning models capture the full complexity of loneliness, moving beyond simple demographic associations.

3.2 Data Processing and Machine Learning Workflow

3.2.1 Data preprocessing and feature engineering

The data processing, as shown in Figure 2, began with raw data collected via the LINE platform. Several critical steps were taken to transform this information into a structured baseline dataset suitable for machine learning. First, a comprehensive data cleaning process was conducted to ensure data integrity. This included handling missing values, identifying outliers, and correcting inconsistencies. After cleaning, feature engineering was applied to extract the most informative features from the raw data. This vital step involved selecting all 12 identified sociodemographic, physiological, and mental health metrics as predictors for the loneliness models. Techniques such as correlation analysis and feature importance methods were employed to assess the predictive value of these variables. Further preprocessing involved applying standard machine learning widgets (e.g., Impute Missing Values, Normalize, Discretize) to scale and prepare the data for subsequent modeling.

3.2.2 Machine learning model development

The structured baseline dataset, which included all 12 engineered features, proceeded to the Data Sampling stage. Here, the dataset was partitioned into a training set (80%) and a testing set (20%), ensuring that model performance could be rigorously evaluated on unseen data. Four distinct machine learning algorithms were selected for model development to predict the degree of loneliness:

- *Logistic Regression:* This linear model predicts the probability of loneliness based on selected predictors, using regularization techniques (L1 or L2) to enhance feature selection and prevent overfitting.

- *Support Vector Machine (SVM):* A non-linear algorithm that identifies optimal decision boundaries to separate individuals into different loneliness classes.

- *Decision Tree:* A foundational algorithm that establishes a hierarchical set of decision rules to segment the data and classify loneliness levels.

- *Random Forest:* An ensemble method that combines multiple decision trees to enhance prediction accuracy, improve generalizability, and reduce the risk of overfitting commonly seen in single-tree models.

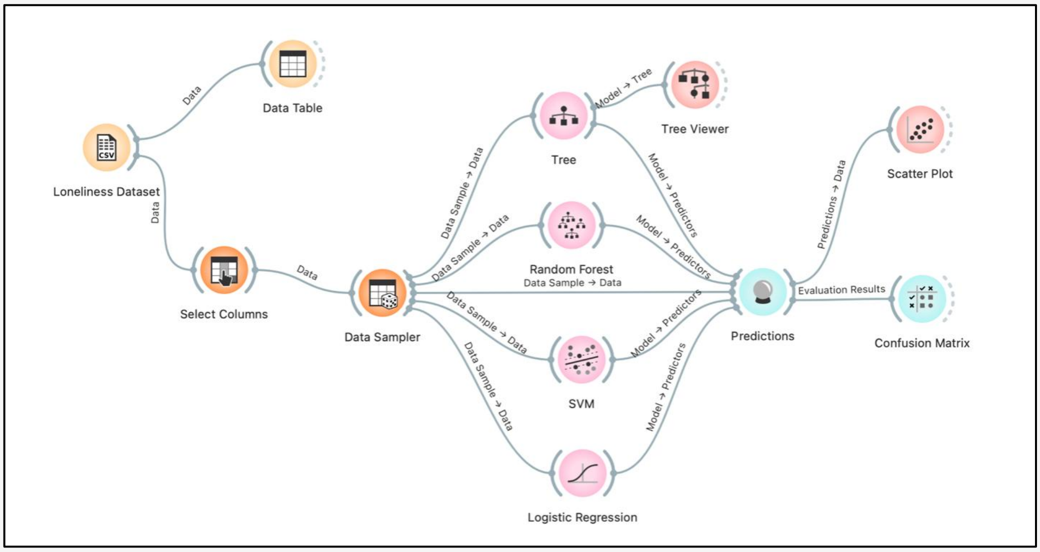

Figure 2: Data Processing and Machine Learning Workflow

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3.2.3 Parameter tuning and model evaluation
To ensure optimal and reliable performance, a rigorous parameter-tuning and optimization process was implemented for each model.

- *SVM:* Optimization involved tuning the regularization parameter (C) and selecting the appropriate kernel type (e.g., linear or radial basis function) to control model complexity and precisely define decision boundaries.

- *Random Forest:* Hyperparameters, including the number of trees (n) and the maximum depth of each tree, were systematically adjusted to minimize prediction errors and mitigate overfitting.

Finally, the models were assessed in the Model Evaluation stage using the unseen testing data. Performance metrics calculated included Accuracy, Precision, Recall, F1-score, AUC (Area Under the Curve), and the Matthews Correlation Coefficient (MCC) to compare model efficacy. The results of this evaluation informed the selection of the best-fit predictive model. Visualization tools, such as the Tree Viewer, were utilized to provide an interpretable view of the model's decision-making process and highlight influential factors, as shown in Table 2.

4. Experiments and Results

4.1 Descriptive Analysis of Influential Factors
To establish a robust empirical basis for the machine learning models, we conducted a detailed descriptive analysis to examine the relationship between sociodemographic variables and the UCLA Loneliness Score. This method ensures that the selection of features is backed by the actual data distribution. Table 3 summarizes the main descriptive results and age profiles.

4.1.1 Gender and marital status
The data indicate that gender influences self-reported loneliness, with females reporting a slightly higher average score of 20.3 than males (18.75). Marital status also emerged as a strong predictor of social connectivity. As shown in Table 3, widowed individuals reported an average loneliness score of 24.57. In contrast, married participants reported the lowest average score of 13.5, highlighting the importance of a stable partnership as a significant protective factor against social isolation. Additionally, higher scores were observed among single individuals (average score = 25.75) and divorced participants (average score = 24.57). All of these figures exceed the overall cohort average.

4.1.2 Work status and living arrangements
Occupational status reveals distinct patterns in levels of isolation. Individuals identified as students (26.35) and government employees (28.82) reported the highest levels of loneliness. The elevated scores among students align with existing literature that links transitional life stages and academic stress to increased feelings of isolation. In contrast, individuals in retirement (12.56) and trade professions (13.22) reported significantly lower scores, suggesting that stable or routine-based non-labor statuses may help mitigate feelings of loneliness. Living arrangements significantly impact levels of loneliness. Individuals living in nursing homes (26.35) or with friends (26.84) reported high levels of loneliness, indicating that communal living does not always ensure meaningful social interaction. In contrast, those living with family members (15.45) had the lowest loneliness scores. This highlights the crucial role of family support within the Thai cultural context.

Table 2: Key Machine Learning evaluation metrics

Metric	Definition
Accuracy	This metric assesses the overall proportion of instances correctly classified.
Precision	Measures the ratio of true positive predictions to all positive predictions made by the model.
Recall (Sensitivity)	Measures the proportion of true positive predictions out of all actual positive cases.
F1-score	Represents the harmonic mean of precision and recall, providing a balanced measure of a model's performance, especially useful with imbalanced classes.
AUC (Area Under the ROC Curve)	Measures the model's ability to distinguish between positive and negative classes. A higher AUC indicates better discriminatory power.
MCC (Matthews Correlation Coefficient)	Calculates the Pearson product-moment correlation coefficient between the true and predicted binary classifications, providing a balanced measure that applies to both balanced and imbalanced datasets.

Table 3: Consolidated analysis of descriptive characteristics and predictor importance

Factor Category	Predictor Variable	Sample Profile / Descriptive Result	Pearson Correlation (r) with Loneliness	V.I.A. Ranking (Predictive Impact)
Mental Health	Depression (9Q/2Q)	High correlation with social withdrawal	+0.17 (p<.001)	1st
Mental Health	Anxiety (TAI)	Bidirectionally linked to social isolation	+0.09 (p=.016)	2nd
Functional	ADL Scale	Primary indicator of functional health	−0.04 (p=.07)	3rd
Demographic	Age	Mean: 60.37 (Not Lonely) vs. 38.69 (Lonely)	−0.44 (p<.001)	5th
Demographic	Marital Status	13.5 (Married) vs. 24.57 (Widowed/Divorced)	−0.31 (p<.001)	6th
Physiological	BMI	Higher BMI linked to reduced mobility	+0.08 (p=.008)	Included
Lifestyle	Exercise Scale	A sedentary lifestyle increases the risk of isolation	−0.02 (p=.314)	Included
Physiological	Blood Pressure	Cardiovascular health metrics (SYS/DIA)	Negligible linear correlation	Included

4.1.3 Age profile by loneliness degree

The analysis of the age distribution shows a significant inverse relationship between age and loneliness severity. As shown in Table 3, the largest group of participants, categorized as "Not Lonely" (Low Degree), consisted of 399 individuals with a mean age of approximately 60.37 years. In contrast, those classified as "Lonely (High Degree)" (N=13) and "Lonely Risk (Moderate Degree)" (N=94) had significantly lower mean ages of 38.69 and 41.63 years, respectively. This pattern suggests that younger adults in this Thai community sample are more susceptible to social isolation compared to their older counterparts.

4.2 Machine Learning Analysis and Predictor Ranking

A preliminary linear regression model that focused solely on Age and Gender demonstrated minimal explanatory power, with an R^2 value of 0.10. This highlights the need for a multi-factor approach. Therefore, a correlation analysis was conducted on all 12 collected factors to assess their relationship with the UCLA Loneliness Score. The details of these relationships are presented in the "Pearson Correlation" column of Table 3.

4.3 Machine Learning Model Performance

Four distinct algorithms were trained using an 80/20 train-test split: Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT). Among these, the Logistic Regression (LR) model demonstrated the strongest overall discriminative power, with the following metrics:

- Classification Accuracy (CA): 0.707
- Area Under the Curve (AUC): 0.697
- Matthews Correlation Coefficient (MCC): 0.253

While LR outperformed the non-linear algorithms, the moderate performance metrics highlight the challenges of predicting subjective states from cross-sectional data. The consistently low MCC values indicate potential difficulties in classifying the less-represented "Moderate" and "High" loneliness categories. The persistently low MCC values across all models underscore the difficulty of reliably classifying the "Moderate Degree" and "High Degree" categories. This situation emphasizes the need for Variable Importance Analysis (V.I.A.) to identify key risk factors.

4.4 Variable Importance Analysis

To address the limitations of moderate predictive performance, we conducted a Variable Importance Analysis (VIA) using a Random Forest model. This analysis ranked the contributions of all 12 input factors. The results of this ranking are presented in the final column of Table 3. The V.I.A. revealed a hierarchy that contrasts sharply with the results obtained from linear correlation analyses. The primary nonlinear drivers identified were psychological and functional. As shown in Table 3, the Depression Scales and the Thai Anxiety Inventory (TAI) ranked first and second, respectively, indicating that mental health issues have the most significant impact on predictive outcomes. Activities of Daily Living (ADLs) ranked third, highlighting that functional impairments severely limit community participation. In contrast, demographic variables such as Age and Marital Status, which exhibited the strongest linear correlations, were ranked lower (fifth and sixth) within the complex machine learning framework.

5. Conclusion and Future Directions

The primary objective of this cross-sectional study was to use machine learning (ML) techniques to identify the key factors influencing loneliness among Thai adults. This approach was necessary because traditional demographic predictors provided limited insights, and simple linear models showed weak explanatory power. In contrast, ML effectively validated a multi-factor predictive model, with Logistic Regression (LR) being the most effective classifier. It achieved a Classification Accuracy (CA) of 0.707 and an Area Under the Curve (AUC) of 0.697. These results suggest that the relationship between the assessed input factors and loneliness in this specific dataset is primarily linear or quasi-linear.

A key outcome of this research is the Variable Importance Analysis (V.I.A.), which established a clear and actionable hierarchy of predictors for loneliness. The analysis indicated that psychological and functional factors specifically depression, anxiety, and Activities of Daily Living (ADLs) are significantly more influential than demographic variables such as age or marital status when it comes to determining the risk of loneliness. In particular, the Depression Scales and the Thai Anxiety Inventory (TAI) were identified as the primary predictors, closely followed by the ADL scale. This evidence strongly suggests that addressing co-occurring mental health issues and overcoming physical functional barriers are the most effective strategies for reducing loneliness in this population. Despite the insights gained, the current model's performance (AUC ≈ 0.70) and low Matthews Correlation Coefficient (MCC) highlight the urgent need for technical and methodological improvements to better identify minority classes, such as individuals experiencing moderate to high levels of loneliness. Therefore, future research will prioritize the following strategic initiatives:

5.1 Model Optimization and Transparency

Future efforts will focus on rigorous hyperparameter tuning of the Logistic Regression model to achieve an AUC greater than 0.85. Additionally, Explainable AI (XAI) techniques will be integrated to clarify the model's decision-making process, thereby helping to build trust among healthcare providers and enhance its clinical utility.

5.2 Longitudinal Validation

To overcome the limitations of cross-sectional studies and formally establish causality, a prospective longitudinal cohort study is necessary. This study will track the incidence and progression of loneliness over a two-to-three year period using the established LINE platform and web-based data collection methods.

5.3 Intervention Validation through Randomized Controlled Trials (RCTs)

RCTs are vital for providing evidence-based policy recommendations. High-risk individuals identified by refined machine learning models will be assigned to personalized, module-based interventions delivered via the LINE application. These interventions will specifically target anxiety reduction and promote physical activity to enhance social well-being. These integrated future steps aim to transform the current predictive tool into a clinically viable system that informs targeted, data-driven public health strategies and social support programs for high-risk demographic groups.

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