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Development and validation of short-term, medium-term, and long-term suicide attempt prediction models based on a prospective cohort in Korea

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A R T I C L E I N F O

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A B S T R A C T

Background: This study aimed to develop and validate prediction models for short-(3 months), medium-(1 year), and long-term suicide attempts among high-risk individuals in South Korea.
Methods: Data from the K-COMPASS cohort, a large prospective study conducted across five medical centers in South Korea between 2015 and 2023, were used. This cohort included 1246 high-risk individuals, with structured clinical assessments and follow-up data collected at multiple time points. Logistic regression and Cox proportional hazards models, along with machine learning methods (random forest, XGBoost, and random survival forest), were applied to predict suicide attempts, with internal and external validations conducted for each model.
Results: In short-term and medium term prediction models, traditional logistic regression models showed moderate accuracy in the training cohort (AUC: 0.7461–0.8708) and lower but acceptable accuracy external validation (AUC: 0.5958–0.7051). Machine learning models showed higher accuracy in the training cohort (AUC: 0.8454–1.0000) but a decrease in the external validation cohort (AUC: 0.5948–0.7030). In long-term prediction, Cox models also demonstrated acceptable predictive accuracy, with a c-index of 0.780–0.786 in the training cohort, which decreased to 0.632–0.663 in the external validation cohort, whereas the random survival forest model showed 0.668–0.706 and 0.633–0.721 in both cohorts. The key predictors included younger age, prior suicide attempts, and psychiatric factors such as depression and anxiety.

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1876-2018/© 2025 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

Conclusions: Both traditional and machine learning models showed high accuracy in the internal validation and lower but acceptable accuracy in the external validation. Data reliance on self-reporting and missing medication specifics may affect prediction precision.

1. Introduction

According to the World Health Organization, more than 800,000 people die by suicide every year or every 40 seconds (World Health Organization, 2023). South Korea recorded the highest suicide rate among the Organisation for Economic Co-operation and Development member countries by 2022 (OECD, 2023). Suicide is a major social problem in South Korea, with a 2018 survey showing that 18.5 % of Koreans have considered suicide, and 2.4 % have actually attempted it (Ahn and Wi, 2019). This country has shown an increase in depression (Kang et al., 2023) and suicidality (Ministry of Health and Welfare, 2023) among the younger age group since the COVID-19 pandemic.

Effective screening of groups at high risk for suicide and providing appropriate psychiatric and social support to these patients are important for suicide prevention. Recent studies have shown that machine-learning-based prediction models can predict suicide risk more accurately than traditional statistical methods (Menon and Vijayakumar, 2023). In a study by Walsh et al. (2017), a random forest model using electronic medical record data showed 84 % accuracy in predicting suicide attempts. In addition, Kessler et al. (2017)) demonstrated in a study of US soldiers that machine-learning algorithms were useful in predicting suicide risk. Other recent studies also demonstrated the utility of machine learning (ML) in predicting suicidality among depressive patients (Yang et al., 2023) and adolescents (Shin and Kim, 2023; Wen et al., 2023). Although machine learning-based suicide risk prediction models have shown promising accuracy, concerns remain regarding their actual impact on suicide prevention (Thornton and Tandon, 2023). Larger prospective cohort studies and validation in diverse populations are required to improve the performance and generalize the results of these models.

In a previous study by our research team, a model was constructed to predict suicide attempts at six months after follow-up observation using logistic models and machine learning models based on prospective cohort data on high-risk suicide groups (Yang et al., 2024). These models focus on predicting risk at a specific point in time without considering changes over time. This study makes an important contribution to the prediction of suicide attempt recurrence, but it has several limitations. The sample size for validation was relatively small, which decreased its reliability. In addition, because the individual items of the clinical scale were used as variables, their reliability and validity were not sufficiently verified. In addition, because the prediction model was only built for a single period of six months without using a time-dependent validation method, there were questions about the generalizability of the prediction model over time. To overcome these limitations, this study aimed to improve the prediction model using the same data but with a more reliable analysis method. We extended the research period, added samples to secure a larger validation sample, and introduced advanced variable selection methods and time-dependent validation. In addition, to evaluate the performance of the prediction model over time, we set new time points of 3 months and 1 year as short-term and mid-term models, respectively, introduced the Cox proportional hazard model and random survival forest to build a long-term model, and verified the predictive power of each model.

The 3-month and 1-year time points were chosen to allow for more precise predictions by considering both short- and mid-term risks for suicide attempts. The 3-month time point is a model predicting short-term suicide risk, which is the average time it takes to treat a major depressive episode (Baldacara et al., 2019b; Furukawa et al., 2000) and the period when the suicide mortality rate remains the highest after discharge from a psychiatric hospital (Chung et al., 2017). In addition, the 1-year point is a model that predicts mid-term suicide risk. It has been reported that suicide risk remains high for one year after discharge from a psychiatric hospital (Choi et al., 2019), and that the suicide death rate within 12 months after self-harm is up to 20 times higher than that of the general population (Olfson et al., 2017).

Short-term risk prediction models are helpful for establishing immediate emergency intervention strategies for high-risk groups (Simon et al., 2021), while long-term risk prediction models are useful for identifying targets that require continuous observation and intervention (Cassells et al., 2005). Therefore, by developing and validating both models, more comprehensive and effective suicide prevention strategies can be established.

Meanwhile, despite many previous studies, clear evidence on whether mental illness treatment, especially medication, actually reduces suicide risk remains lacking (D'Anci et al., 2019; Gibbons and Mann, 2011; Thaker et al., 2015). Among suicide victims, the use of psychotropic drugs, such as antidepressants and tranquilizers, is known to be higher than that in the general population (Culpepper et al., 2004). This can be interpreted as reverse causality because people receiving psychiatric treatment have more severe mental symptoms that directly affect suicide, such as depression. However, the extent to which this can be attributed to the confounding effect is not clear. To confirm the suicide prevention effects of psychiatric drug treatment, it is necessary to build and analyze statistical models that do not include psychiatric drug treatment.

This study aimed to develop short-, medium-, and long-term prediction models for suicide attempts in high-risk groups. The generalizability of the model was assessed using a time-dependent validation method and the accuracy of the prediction model was improved using a more objective and reliable variable selection method. In addition, we aimed to verify the accuracy of the model constructed in this manner in a separate, independently constructed cohort.

2. Methods

2.1. Research participants

The Korean Cohort for the Model Predicting Suicide and Suicide-Related Behavior (K-COMPASS) study is a long-term, large-scale, multi-institutional prospective study that began in 2015 and is the first prospective cohort study in the field of suicide research in South Korea (Park et al., 2019). The K-COMPASS study was conducted among suicidal ideators and suicide attempters. The study participation conditions were set as those who had attempted suicide within the past month, were currently thinking about suicide, and were aged 15 years or older at the time of the initial assessment. The exclusion criteria included a history of intellectual disability or organic brain disease and an inability to communicate in Korean.

Participants were recruited from eight university hospitals and eight mental health and welfare centers in South Korea. Hospitals and centers were selected from eight main regions nationwide, and participants were recruited from outpatients, wards, and emergency rooms in hospitals. The first cohort was recruited from September 1, 2015, to August 31, 2019; the second cohort was recruited from September 1, 2019, to June 30, 2022; and the third cohort was recruited from July 1, 2022, to December 30, 2023.

2.2. Evaluation schedule

During the first year from the date of enrollment, the study participants were initially assessed in the first month after enrollment and then every 3 months (3, 6, 9, and 12 months). One year after enrollment, the study participants were assessed at 6-month intervals starting at 18 months and then at 24, 30, 36, 42, and 48 months.

2.3. Variables for analysis

All the participants underwent an initial assessment through a structured interview with a trained assessor. The trained assessors included mental health nurses and social workers, all of whom underwent specialized rater training prior to their involvement in the study assessments. Demographic information (age, sex, marital and residential status, educational level, monthly household income, and employment status) and clinical information (physical and psychiatric disorders, psychiatric treatment and hospitalization, family history, and suicide attempts) were collected through self-reports. Psychiatric treatment was defined as any psychiatric treatment including pharmacological treatment and psychotherapy.

Other systematic assessment tools included the Columbia-Suicide Severity Rating Scale (C-SSRS) (Jang et al., 2014; Posner et al., 2011), to assess suicide risk, the Mini International Neuropsychiatric Interview (MINI) as a structured psychiatric diagnostic tool (Yoo et al., 2006), the Patient Health Questionnaire-9 (PHQ-9) to assess depressive symptoms (Ahn et al., 2013; Kroenke et al., 2001; Park et al., 2010), the Beck Anxiety Inventory (BAI) to assess anxiety symptoms (Beck et al., 1988; Yook and Kim, 1997), the Alcohol Use Disorders Identification Test (AUDIT) to assess alcohol use problems(Chang et al., 2016), the Social Relation Scale (SRS) to assess social relationships (Lee et al., 2010), the Stress Questionnaire for Korean National Health and Nutrition Examination Survey-Short Form (SQ for KNHANES-SF) to assess stressful situations (Heo, 2019), the Early Trauma Inventory Self-Report-Short Form (ETISR-S) to assess childhood trauma (Jeon et al., 2012), and the Barratt Impulsiveness Scale-11 (BIS-11) to assess impulsivity (Lee et al., 2012; Patton et al., 1995).

To build a three-level hierarchical statistical model, these variables were classified as follows:

Model 1): Demographic and clinical variables

Includes age, sex, marital status, education, employment, religion, cohabitation, region, physical illness, mental illness, suicide attempt history, family history of mental illness, suicide attempts, and suicide death.

In actual clinical practice, there may not be sufficient time to use psychiatric scales, and for screening large populations, statistical models that utilize only basic variables without using psychiatric scales may be advantageous.

Model 2): Demographic and clinical variables and psychiatric assessment tools

Uses the variables in Model 1) along with K-MINI diagnosis, C-SSRS severity and intensity, PHQ-9, BAI, AUDIT, BIS-11, ETI, and SQ for KNHANES-SF and SRS.

To increase the accuracy of the model compared to Model (1), a model was constructed that included psychiatric assessment tools reflecting the current psychopathological status, including suicidal thoughts.

Model 3): Demographic and clinical variables, psychiatric assessment tools, and psychiatric treatment status.

Builds on Model 2) by adding current psychotropic drug use.

2.4. Statistical methods

2.4.1. Statistical analysis

To compare demographic, clinical, and psychiatric characteristics between suicide attempters and non-suicide attempters during the follow-up period, the chi-square test was used for categorical variables and the Student's *t*-test was used for continuous variables. The Statistical Package for the Social Sciences version 21.0 for Windows (SPSS, Inc., Chicago, IL, USA) was used for statistical analysis. Statistical significance was set at $P < 0.05$.

2.4.2. Variable selection: SHAP value

SHAP is the abbreviation for SHapley Additive exPlanation. This is an additive distribution method regardless of the model class. The SHAP values indicate the degree to which each input variable contributes to the model prediction; thus, they can facilitate the interpretation of the model. A positive value indicates an increase in prediction risk, and a negative value indicates a decrease in risk (Lundberg, 2017).

This analysis used five, 10, and 15 different variable sets to obtain the SHAP value to build the prediction models. It is considered inefficient to use more than 15 variables, including clinical scales, in actual clinical practice; therefore, variable sets of more than 15 variables were not calculated. For each variable set, the Area Under the Curve (AUC) was calculated for the short- and medium-term prediction models, and Harrel's concordance index (c-index) (Longato et al., 2020) was calculated for the long-term prediction models. The number of variables that maximized this value was five, 10, and 15. SHAP values were calculated using the Survex package in R 4.3.2. (Supplementary Table 1)

2.4.3. Model building and verification

Based on variables 1), 2), and 3) of the first cohort, statistical models were constructed to predict suicide attempts at 3 months and 1 year during the follow-up and throughout the entire follow-up period. The 3-month and 1-year time points were selected based on clinical evidence highlighting that suicide risk peaks within three months post-discharge from psychiatric hospitals and remains elevated for up to one year, (Choi et al., 2019; Chung et al., 2017) aligning with the typical treatment duration for major depressive episodes (Baldacara et al., 2019a; Furukawa et al., 2000). For short- and mid-term risk prediction, traditional multivariate logistic regression models and machine learning techniques, such as random forests (Biau and Scornet, 2016) and XGBoost (Tianqi Chen, 2016) were applied to the first cohort data. The statistical model built from the first cohort data was applied to the second and third cohort data to check whether accurate variables, such as the area under the curve (AUC), sensitivity, and specificity, were still acceptable. The analysis was performed using R (version 3.6.3) and Python (version 2.7.17), and statistical significance was set at $p < 0.05$.

For long-term risk prediction, the traditional Cox regression and random survival forest models using machine learning techniques were applied to the first cohort data. The statistical model built from the first cohort data was applied to the first, second, and third cohort data to calculate the C-index and Brier score (Brier, 1950) to verify the model's prediction performance and classification ability.

The Brier score is a statistical measure of probabilistic prediction accuracy. It is calculated as the mean squared error between the predicted probability and the actual outcome and has a value between 0 and 1. A score of 0 represents a perfect prediction and 1 represents the worst prediction. Therefore, the lower the Brier score, the more accurate the prediction. In terms of interpretation of the Brier score, a value of 0.1 or less indicates very good prediction accuracy. In general, a Brier score of 0.2 or less suggests that the model provides useful predictions (Steyerberg et al., 2010).

SAS statistical software (version 9.4; SAS Institute Inc., Cary, NC, USA) and R software (R for Windows, version 4.3.2) were used to build the Cox proportional hazard model. Random survival forest analysis was performed using the randomForestSRC package in R, version 4.3.2. STATA 15.0 (StataCorp). 2017. Stata Statistical Software: Release 15. College Station, TX, StataCorp LLC) was used to construct the calibration curve.

2.5. Ethics statement

The study protocol was approved by the Seoul National University Hospital Institutional Review Board (H-1505–050–671) and the

Institutional Review Boards of all participating study sites. This study was conducted according to the principles of the Declaration of Helsinki. For adolescents under 19 years of age, the participants or their legal guardians provided written informed consent.

3. Results

3.1. Comparison of baseline characteristics of research participants

For the 3-month suicide attempt prediction model, a statistical model was built for 437 participants from among 800 participants in the Phase 1 cohort who continued to be followed up for 3 months after the initial assessment, and the built model was verified for 229 participants from among 446 participants in the Phase 2–3 cohort who continued to be followed up for 3 months. For the 1-year suicide attempt prediction model, a statistical model was constructed for 273 participants in the Phase 1 cohort who continued to be followed up for 3 months after the initial assessment, and the constructed model was verified for 59 participants in the phase 2–3 cohort who continued to be followed up for 1 year. For the long-term survival analysis, a statistical model was built for 583 participants in the Stage 1 cohort who visited at least once after the initial evaluation, and the built model was verified for 362 participants in the Stage 2 and 3 cohorts who visited at least once after the initial evaluation. Evaluations were conducted for up to 1107 days in the Phase 1 cohort and 1828 days in the Phase 2 and 3 cohorts.

The 3-month follow-up results showed that participants in the first stage were older, had a higher proportion of males, and had a lower socioeconomic status than participants in the second and third stages (Supplementary Table 2). Additionally, they had a higher frequency of physical illness, but lower rates of psychiatric illness and medication use (Supplementary Table 3). Regarding psychiatric diagnoses, participants in the second and third stages had higher rates of major depressive episodes and suicide risk. Overall, first-stage participants had more physical illnesses but lower psychiatric severity and suicide risk. These trends were consistent across both participants at 1-year and the entire follow-up period (Supplementary Tables 4–7).

3.2. Univariate logistic regression and Cox proportional hazard models

In the 3-month model, the main variables predicting suicide attempts were living with non-family members (OR=3.775), younger age (OR=0.953), suicide attempts within the past month (OR=4.032), lifetime suicide attempts (OR=7.151), use of psychiatric medication (OR=4.931), and poor medication compliance (OR=7.150) (Table 1). In the 1-year model, lower age (OR=0.950), suicide attempt within the past month (OR=2.667), lifetime suicide attempts (OR=4.834), major depressive episode (OR=9.247), recurrent depressive episodes (OR=3.472), hypomanic episode (OR=5.867), high suicide risk assessed with MINI (OR=6.563), and suicidal ideation intensity (OR=1.084) and severity (OR=1.368) were found to be significant predictive factors (Table 2).

In the survival analysis, the risk of suicide attempts decreased with increasing age (HR=0.963), and the risk of suicide attempts was lower when married or widowed. (HR=0.493, HR=0.213), and increased with a secondary school diploma (HR=8.185). Mental health-related variables included recent suicide attempt history within the past month (HR=1.789), lifetime suicide attempt history (HR=5.589), history of mental illness (HR=3.365), and use of psychiatric medication (HR=4.837) as risk factors for suicide attempts. Structured assessment items included major depressive episode (HR=2.648), recurrent depressive episode (HR=2.251), suicide risk (HR=2.58), hypomanic episode (HR=2.343), posttraumatic stress disorder (HR=2.41), childhood trauma (HR=1.803), intensity of suicidal ideation (HR=1.124), severity (HR=1.335), and anxiety (HR=1.02) as factors that significantly predicted suicide attempts (Table 3).

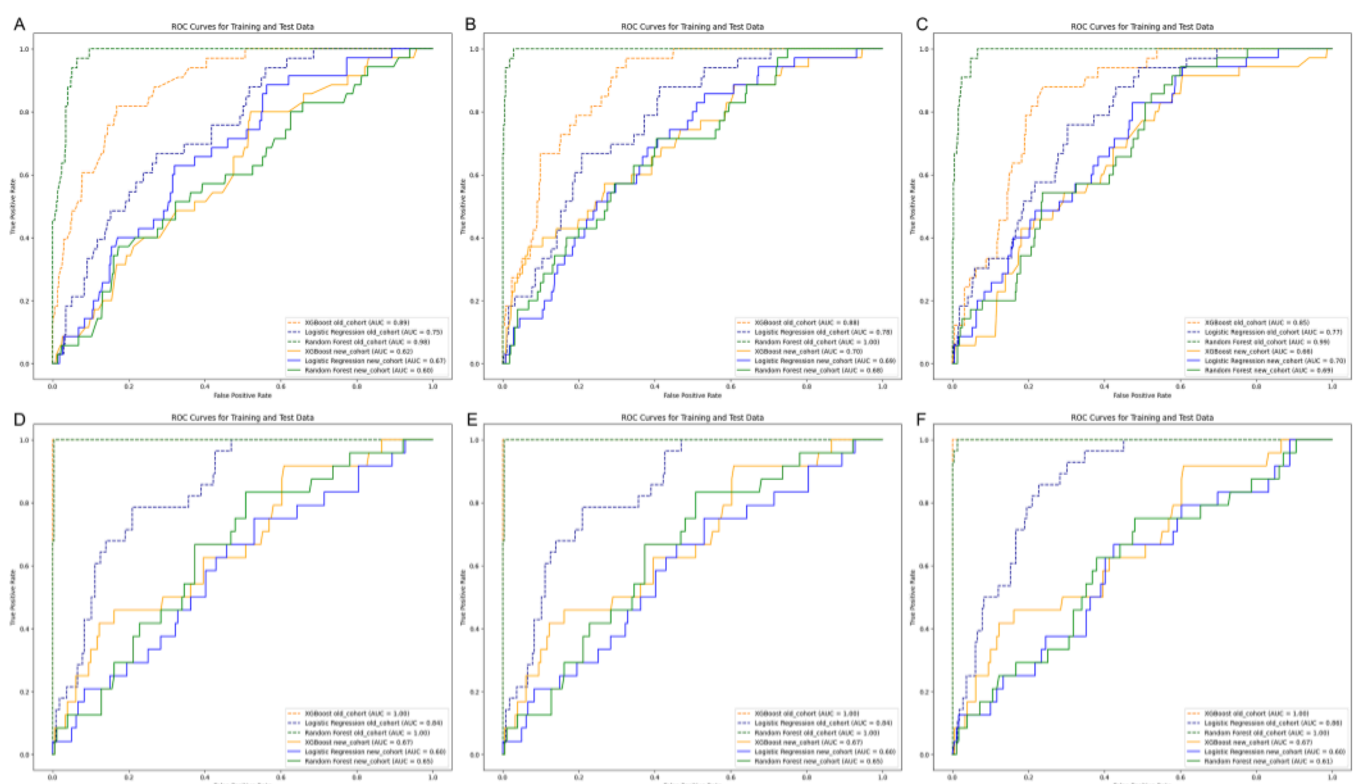

Fig. 1. ROC curves for prediction models for suicide attempt. A) within 3 months in 1st and 2nd wave of the study, using only sociodemographic variables, B) using sociodemographic and clinical variables, C) using all variables, including psychotropic use. D) within 12 months in 1st and 2nd wave of the study, using only sociodemographic variables, E) using sociodemographic and clinical variables, F) using all variables, including psychotropic use.

Table 1
Odds ratio of suicide attempts predicted through univariate logistic regression model for suicide attempt within 3 months.

Variable	OR			95 % C.I		p-value
Age			0.953	0.929	0.977	**< .0001**
Sex (ref=male)						
Female			0.769	0.392	1.507	0.444
Marriage (ref=Not married)						
Currently married			0.623	0.343	1.133	0.121
Education (ref=less than elementary)						
Elementary school			2.518	0.253	25.028	0.431
Middle school			2.938	0.333	25.920	0.332
High school			3.948	0.518	30.054	0.185
More than college			2.697	0.323	22.511	0.360
With occupation (ref=Without occupation)						
With occupation			1.085	0.551	2.136	0.813
Religion (ref=not religious)						
Religious			0.950	0.485	1.859	0.881
Living status (ref=Living with family)						
Living with non-family			3.775	1.006	14.168	**0.049**
Living in a facility			5.034	0.984	25.739	0.052
Living alone			1.182	0.557	2.507	0.663
Cohabitant (ref=Living alone)						
Living not alone			0.991	0.479	2.054	0.981
Residence (ref=urban)						
Living in rural area			1.158	0.436	3.074	0.769
Income			1.000	0.999	1.002	0.526
Medical & Psychiatric						
History of physical illness			0.339	0.157	0.732	**0.006**
History of psychiatric illness			1.858	0.644	5.360	0.252
Current psychotropic use			4.931	1.169	20.801	**0.030**
Drug compliance (ref=0 %)						
- 0–25 %			4.469	0.941	21.221	0.060
- **25–50 %**			7.150	2.217	23.058	**0.001**
- 50–75 %			2.616	0.850	8.045	0.093
- 75–100 %			0.872	0.191	3.971	0.859
Suicidal						
Recent suicidal attempt within a month	4.032	1.404	11.494	1.087	14.942	**0.010**
Lifetime history of suicidal attempt			7.151	1.701	30.084	**0.007**
Familial						
History of psychiatric illness			1.546	0.767	3.117	0.223
History of suicidal attempt			1.152	0.544	2.442	0.711
History of suicide completion			1.085	0.439	2.680	0.859
K-MINI Diagnosis						
Current MDE			2.583	1.059	6.303	**0.037**
Recurrent MDE			1.841	0.892	3.800	0.099
Melancholic MDE			1.518	0.729	3.158	0.265
Suicide risk			1.948	0.676	5.618	0.217
- No						
- Mild			0.264	0.029	2.408	0.238
- Moderate			1.218	0.347	4.280	0.758
- Severe			2.479	0.840	7.316	0.100
Current manic episode			0.743	0.097	5.697	0.775
Past manic episode			1.604	0.541	4.759	0.395
Current hypomanic episode			0.615	0.081	4.674	0.638
Past hypomanic episode			1.083	0.408	2.872	0.873
Current PTSD			2.281	0.756	6.890	0.144
Current alcohol dependence			1.392	0.522	3.717	0.509
Current alcohol abuse			0.520	0.070	3.850	0.522
Mood disorder with psychotic features			0.743	0.097	5.697	0.775
Clinical scales						
C-SSRS						
- Severity			1.171	0.946	1.451	0.148
- **Intensity**			1.097	1.017	1.183	**0.017**
PHQ−9			1.028	0.976	1.083	0.294
BAI			1.024	1.002	1.047	**0.033**
AUDIT			1.035	1.006	1.064	**0.017**
BIS−11			1.026	0.999	1.053	0.062
ETISR-SF			2.900	1.252	6.719	**0.013**
SQ for KNHANES-SF			1.033	0.994	1.075	0.095
SRS			0.968	0.865	1.083	0.576

*Variables with $p < 0.05$ are expressed in **bold**.

*Abbreviations: MDE: Major Depressive Episode, C-SSRS: Columbia-Suicide Severity Rating Scale, PHQ-9: Patient Health Questionnaire-9, BAI: Beck Anxiety Inventory, SRS, AUDIT: Alcohol Use Disorder Identification Test, BIS: Barratt Impulsiveness Scale, ETISR-SF: Early Trauma Inventory Self Report-Short Form, SQ-KNHANES: Stress Questionnaire for Korean National Health and Nutrition Examination Survey, SRS: Social Relationship Scale

Table 2
Odds ratio of suicide attempts predicted through univariate logistic regression model for suicide attempt within 12 months.

Variable	OR	95 % C.I		p-value
Age	0.950	0.924	0.975	**< .0001**
Sex (ref=male)				
Female	0.676	0.317	1.445	0.312
Marriage (ref=Not married)				
Currently married	0.585	0.196	1.745	0.337
Education (ref=less than elementary)				
Elementary school	0.854	0.052	14.154	0.912
Middle school	4.516	0.479	42.606	0.188
High school	5.625	0.725	43.641	0.099
More than college	4.200	0.484	36.452	0.193
With occupation (ref=Without occupation)				
With occupation	0.963	0.452	2.050	0.922
Religion (ref=not religious)				
Religious	0.770	0.360	1.649	0.502
Living status (ref=Living with family)				
Living with non-family	0.000	0.000	0.000	0.999
Living in a facility	2.733	0.271	27.550	0.394
Living alone	0.785	0.344	1.795	0.566
Cohabitant (ref=Living alone)				
Living not alone	1.253	0.552	2.846	0.589
Residence (ref=urban)				
Living in rural area	1.145	0.414	3.168	0.794
Income	1.001	1.000	1.002	0.073
Medical & Psychiatric				
History of physical illness	1.048	0.975	1.126	0.197
History of psychiatric illness	2.313	0.677	7.909	0.181
Current psychotropic use	0.756	6.653	0.146	0.756
Drug compliance (ref=0 %)				
- 0–25 %	2.215	0.388	12.654	0.371
- 25–50 %	2.880	0.853	9.718	0.088
- 50–75 %	1.862	0.649	5.344	0.248
- 75–100 %	0.436	0.049	3.885	0.457
Suicidal				
Recent suicidal attempt within a month	2.667	1.192	5.952	**0.017**
Lifetime history of suicidal attempt	4.834	1.429	16.363	**0.011**
Familial				
History of psychiatric illness	0.995	0.918	1.079	0.903
History of suicidal attempt	1.706	0.739	3.935	0.210
History of suicide completion	0.998	0.990	1.007	0.716
K-MINI Diagnosis				
Current MDE	9.247	2.158	39.607	**0.003**
Recurrent MDE	3.472	1.376	8.767	**0.008**
Melancholic MDE	2.144	0.891	5.155	0.088
Suicide risk	3.105	0.913	10.559	0.070
- No				
- Mild	0.656	0.058	7.448	0.734
- Moderate	3.557	0.711	17.796	0.122
- **Severe**	6.563	1.481	29.049	**0.013**
Current manic episode	1.291	0.153	10.859	0.814
Past manic episode	2.632	0.905	7.652	0.076
Current hypomanic episode	5.867	1.328	25.894	**0.020**
Past hypomanic episode	0.996	0.283	3.501	0.995
Current PTSD	2.330	0.471	11.519	0.299
Current alcohol dependence	1.571	0.506	4.874	0.435
Current alcohol abuse	2.606	0.685	9.924	0.160
Mood disorder with psychotic features	1.312	0.367	4.688	0.676
Clinical scales				
C-SSRS				
- **Severity**	1.368	1.076	1.740	**0.011**
- **Intensity**	1.084	1.000	1.176	**0.049**
PHQ−9	1.025	0.969	1.083	0.383
BAI	1.016	0.992	1.041	0.187
AUDIT	1.018	0.982	1.055	0.332
SRS	0.902	0.803	1.014	0.083
SQ for KNHANES-SF	1.060	1.013	1.110	**0.011**
BIS−11	1.022	0.993	1.052	0.139
ETISR-SF	3.849	1.430	10.360	0.008

*Variables with $p < 0.05$ are expressed in **bold**.
*Abbreviations: MDE: Major Depressive Episode, C-SSRS: Columbia-Suicide Severity Rating Scale, PHQ-9: Patient Health Questionnaire-9, BAI: Beck Anxiety Inventory, SRS, AUDIT: Alcohol Use Disorder Identification Test, BIS: Barratt Impulsiveness Scale, ETISR-SF: Early Trauma Inventory Self Report-Short Form, SQ-KNHANES: Stress Questionnaire for Korean National Health and Nutrition Examination Survey, SRS: Social Relationship Scale

3.3. Variable selection based on SHAP value

For short- and medium-term risk analyses, the average AUC was most satisfactory when 10 variables were used for 3 months and 15 variables were used for 1 year; therefore, we decided to use 10 and 15 variables, respectively. For long-term risk analysis, the average c-index was most satisfactory when 15 variables were used for the Cox model and 10 variables were used for the random survival forest model; therefore, we decided to use 15 and 10 variables, respectively (Supplementary Table 1).

The y-axis in Supplementary Figures 1–24 represents each feature and the x-axis represents the SHAP value. In the graph, the features are sorted according to their influence on the prediction, that is, their importance.

Important variables in the short-term prediction were age, income level, cohabitation status, place of residence, history of suicide attempt, history of mental illness, and suicide death in the family, and those in the medium-term prediction were age, education level, income level, cohabitation status, history of suicide attempt, and major depression. Episodes, severity, and intensity of suicidal thoughts have emerged as important variables. Age, cohabitation status, marital status, educational level, history of mental illness, history of suicide attempts, and death in the family were identified as important variables for long-term prediction. Age was the most important protective factor in all models, and clinical measures related to suicidal ideation, mental status, and medication compliance served as key variables.

For the 3-month short-term prediction model, the top 10 variables with the highest SHAP values were selected to build the model. For the 1-year medium-term prediction model, 15 variables were chosen. In the long-term prediction, 15 variables were used in the Cox model, while 10 variables were used in the random survival forest model.

3.4. Performance of suicide attempt prediction models over time across cohorts

A total of 75 participants in the first cohort and 59 participants in the second and third cohorts attempted suicide during the follow-up period. Among the participants in the first cohort, 31 attempted suicide within 3 months, and 40 attempted suicides within one year. Among the participants in the second and third cohorts, 10 attempted suicides within 3 months, and 17 attempted suicides within one year.

Table 4 shows the performance of various statistical and machine learning models in predicting short-term and medium-term suicide attempts. In models predicting suicide attempts three months and one year later for the first cohort and the second and third cohorts, respectively, the AUCs of Random Forest and While very high at 0.8454–0.8892/1 year 0.9842–1.0000, the logistic regression model recorded an AUC of 0.7461–0.7787/1 year 0.7461–0.7787/1 year 0.8189–0.8708. However, when these models were applied to the second and third populations, the accuracy decreased, with AUC for Random Forest being 0.5948–0.6872/1 year, 0.6094–0.6776 for 3 months, and XGBoost, 0.6209–0.7030/1 year, 0.6513–0.6682. The logistic regression model was measured as 0.6528–0.6979 at 3 months and 0.5957–0.7051 at 1 year.

Supplementary Tables 8 to 10 present Cox proportional hazards models based on the first cohort data. Characteristically, Supplementary Table 10 shows that, compared to not taking medication, the risk of suicide attempts was higher when taking medication, but as medication

Table 3
Hazard ratio of suicide attempts predicted through univariate Cox regression model.

Variable	Unadjusted HR	95 % C.I		p-value
Age	0.963	0.95	0.977	**< .0001**
Sex (ref=male)				
Female	1.185	0.742	1.893	0.4777
Marrage (ref=Never Married)				
Currently married	0.493	0.259	0.876	**0.0245**
Cohabitating	0.347	0.003	2.416	0.4655
Separated	0.423	0.048	1.563.	0.4655
Divorced	0.721	0.37	1.301	0.3124
Widowed	0.213	0.044	0.627	**0.0198**
Marriage (ref=Not married)				
Currently married	0.623	0.343	1.133	0.121
Education (ref=less than elementary)				
Elementary school	5.788	0.696	48.111	0.1042
Middle school	8.185	1.022	65.573	**0.0477**
High school	12.648	1.74	91.958	**0.0122**
More than college	9.67	1.274	73.411	**0.0282**
Occupational status (ref=Without occupation)				
With occupation	1.228	0.778	1.938	0.3785
Religion (ref=not religious)				
Religious	0.845	0.535	1.336	0.4712
Living status (ref=Living with family)				
Living with non-family	2.188	0.787	6.079	0.1332
Living in a facility	1.779	0.553	5.724	0.334
Living alone	1.042	0.627	1.733	0.8741
Cohabitant (ref=Living alone)				
Living not alone	1.027	0.625	1.69	0.9151
Residence (ref=urban)				
Living in rural area	0.478	0.207	1.104	0.0838
Income	1.001	1	1.001	0.0686
Medical & Psychiatric				
History of physical illness	0.381	0.233	0.623	**0.0001**
History of psychiatric illness	3.365	1.46	7.757	**0.0044**
Current psychotropic use	4.837	2.098	11.148	**0.0002**
Drug compliance (ref=0 %)				
- **0–25 %**	6.305	1.221	32.545	**0.0279**
- **25–50 %**	5.968	1.821	19.555	**0.0032**
- **50–75 %**	6.54	2.441	17.517	**0.0002**
- **75–100 %**	4.904	1.942	12.385	**0.0008**
Suicidal				
Recent suicidal attempt within a month	1.789	0.349	0.896	**0.0157**
Lifetime history of suicidal attempt	5.589	2.425	12.879	**< .0001**
Familial				
History of psychiatric illness	1.414	0.847	2.359	0.1847
History of suicidal attempt	1.054	0.541	2.051	0.8777
History of suicide completion	1.732	1.059	2.832	**0.0286**
K-MINI Diagnosis				
Current MDE	2.648	1.502	4.668	**0.0008**
Recurrent MDE	2.251	1.369	3.702	**0.0014**
Melancholic MDE	1.62	0.985	2.665	0.0573
Suicide risk	2.58	1.185	5.621	0.017
- No				
- Mild	0.351	0.073	1.688	0.1913
- **Moderate**	2.506	1.011	6.213	**0.0474**
- **Severe**	3.488	1.582	7.688	**0.002**
Current manic episode	1.052	0.331	3.341	0.9312
Past manic episode	1.467	0.674	3.195	0.3342
Current hypomanic episode	2.343	1.017	5.399	0.0456
Past hypomanic episode	1.892	0.971	3.687	0.0611
Current PTSD	2.41	1.106	5.251	0.0268
Current alcohol dependence	1.295	0.665	2.521	0.4468
Current alcohol abuse	1.622	0.745	3.532	0.2234
Mood disorder with psychotic features	1.643	0.789	3.421	0.1845
Clinical scales				
C-SSRS				
- **Severity**	1.335	1.149	1.551	0.0002
- **Intensity**	1.124	1.064	1.188	< .0001
PHQ−9	1.028	0.994	1.064	0.1076
BAI	1.02	1.006	1.034	0.0054
AUDIT	1.028	1.009	1.047	0.0034
SRS	0.953	0.888	1.024	0.1896
SQ for KNHANES-SF	1.043	1.016	1.07	0.0014
BIS−11	1.023	1.007	1.04	0.0054
ETISR-SF	1.803	1.035	3.141	0.0373

*Variables with $p < 0.05$ are expressed in **bold**.
*Abbreviations: MDE: Major Depressive Episode, C-SSRS: Columbia-Suicide Severity Rating Scale, PHQ-9: Patient Health Questionnaire-9, BAI: Beck Anxiety Inventory, SRS, AUDIT: Alcohol Use Disorder Identification Test, BIS: Barratt Impulsiveness Scale, ETISR-SF: Early Trauma Inventory Self Report-Short Form, SQ-KNHANES: Stress Questionnaire for Korean National Health and Nutrition Examination Survey, SRS: Social Relationship Scale

Table 4
Accuracy, sensitivity, specificity, and AUC of prediction models for suicide attempt in 1st and 2nd-3rd wave of the study.

	Accuracy	Sensitivity	Specificity	AUC
3 months, 1st wave				
- Logistic regression, model 1)	0.8153	0.4242	0.8499	0.7461
- Logistic regression, model 2)	0.8547	0.3030	0.9035	0.7787
- Logistic regression, model 3)	0.8571	0.3030	0.9062	0.7738
- Random forest, model 1)	0.9360	0.9091	0.9383	0.9786
- Random forest, model 2)	0.9655	1.0000	0.9625	0.9971
- Random forest, model 3)	0.9557	0.9091	0.9598	0.9899
- XGBoost, model 1)	0.8916	0.5152	0.9249	0.8892
- XGBoost, model 2)	0.8818	0.3636	0.9276	0.8795
- XGBoost, model 3)	0.8448	0.3333	0.8901	0.8454
3 months, 2nd−3rd wave				
- Logistic regression, model 1)	0.7952	0.3429	0.8368	0.6528
- Logistic regression, model 2)	0.7639	0.4000	0.7974	0.6881
- Logistic regression, model 3)	0.7566	0.4571	0.7842	0.6979
- Random forest, model 1)	0.7301	0.3714	0.7632	0.5948
- Random forest, model 2)	0.7976	0.3429	0.8395	0.6823
- Random forest, model 3)	0.7831	0.2286	0.8342	0.6872
- XGBoost, model 1)	0.8265	0.1714	0.8868	0.6209
- XGBoost, model 2)	0.7904	0.4286	0.8237	0.7030
- XGBoost, model 3)	0.8120	0.2857	0.8605	0.6627
12 months, 1st wave				
- Logistic regression, model 1)	0.8436	0.7143	0.8605	0.8708
- Logistic regression, model 2)	0.8395	0.6429	0.8651	0.8409
- Logistic regression, model 3)	0.8189	0.6071	0.8465	0.8189
- Random forest, model 1)	0.8313	1.0000	0.8093	0.9842
- Random forest, model 2)	0.9383	1.0000	0.9302	0.9985
- Random forest, model 3)	0.9383	1.0000	0.9302	0.9993
- XGBoost, model 1)	0.8313	1.0000	0.8093	0.9842
- XGBoost, model 2)	0.8683	1.0000	0.8512	0.9985
- XGBoost, model 3)	0.8889	1.0000	0.8744	1.0000
12 months, 2nd−3rd wave				
- Logistic regression, model 1)	0.7044	0.5833	0.7207	0.7051
- Logistic regression, model 2)	0.7438	0.2500	0.8101	0.5957
- Logistic regression, model 3)	0.7094	0.3750	0.7542	0.5958
- Random forest, model 1)	0.7980	0.3333	0.8603	0.6776
- Random forest, model 2)	0.7241	0.3750	0.7709	0.6471
- Random forest, model 3)	0.7389	0.2917	0.7989	0.6094
- XGBoost, model 1)	0.7635	0.4167	0.8101	0.6513
- XGBoost, model 2)	0.8128	0.4167	0.8659	0.6682
- XGBoost, model 3)	0.8128	0.4167	0.8659	0.6661

adherence increased, the proportional hazard ratio decreased. Table 5 summarizes the accuracy values when the random survival forest model, as well as the Cox models, built on the first cohort data, is applied to data from both the first cohort and the second and third cohorts, In predicting suicide attempts using the Cox proportional hazards model, all three models recorded high performance, with a C-Index of 0.780–0.786 when applied to the first population; however, the C-Index was 0.632–0.663 in the second and third populations. decreased. The Brier score was found to be 0.069–0.273, and Model 1) had the lowest score at all time points

Table 5
C-index and Brier score of Cox proportional hazard models and random survival forest models in 1st and 2nd-3rd wave.

	Cox proportional hazard models	Random survival forest models
Model 1		
- C-index (1st wave)	0.780	0.706
- C-index (2nd & 3rd wave)	0.663	0.633
- Brier score at 3 month	0.069	0.061
- Brier score at 6 month	0.098	0.093
- Brier score at 1 year	0.136	0.118
- Brier score at 2 year	0.206	0.145
Model 2		
- C-index (1st wave)	0.784	0.668
- C-index (2nd & 3rd wave)	0.656	0.721
- Brier score at 3 month	0.123	0.067
- Brier score at 6 month	0.166	0.109
- Brier score at 1 year	0.231	0.124
- Brier score at 2 year	0.273	0.192
Model 3		
- C-index (1st wave)	0.786	0.682
- C-index (2nd & 3rd wave)	0.632	0.671
- Brier score at 3 month	0.136	0.075
- Brier score at 6 month	0.187	0.122
- Brier score at 1 year	0.256	0.132
- Brier score at 2 year	0.214	0.193

and showed a tendency to increase over time from 3 months to 2 years at most time points. The model using Random Survival Forest (RSF) also showed an excellent C-Index (0.668–0.706) and Brier score (0.061–0.193) in the first population, but its performance decreased in the second and third populations. The Brier score was also the lowest in Model 1), and tended to increase over time from 3 months to 2 years.

4. Discussion

In this study, we constructed statistical models that can predict high-risk groups for suicide attempts within 3 months and 1 year, both in hospital and community settings using the "traditional" logistic regression model as well as machine learning-based models like random forest and XGBoost. In addition, we constructed prediction models for the long-term high-risk group of suicide attempters using the "traditional" Cox survival model and a machine learning-based random survival forest model. The constructed models showed excellent accuracy in the original dataset; however, the accuracy decreased significantly in the 2–3 cohort, although it still showed an acceptable level of accuracy.

The subjects recruited in Phases 2 and 3 were younger and more likely to be female, had a higher prevalence and treatment rates of mental disorders, and had higher psychopathology scores than those recruited in Phase 1. Recruitment in Phases 2 and 3 began in September 2019, coinciding with the COVID-19 pandemic that began in China in December 2019. Since the onset of the COVID-19 pandemic, suicide rates among the elderly have decreased, but suicide rates among young people and women have increased, a trend that has been repeatedly observed in studies in Korean countries (Kim et al., 2023; Park et al., 2023; Ryu et al., 2022; Czeisler et al., 2020; Osaki et al., 2021; Sahoo and Patra, 2023; Tanaka and Okamoto, 2021; Yard et al., 2021). In addition, as the prevalence of mental illness and mental symptoms increases, mental health problems have become a major issue (Czeisler et al., 2020). The changes in the tendencies of the high-risk group for suicide shown in this study were consistent with the results reported in previous studies.

Age was identified as the most important protective factor against suicide attempts in both the SHAP value analysis and the short-, medium-, and long-term risk prediction models. Previous studies have shown that the risk of suicide attempts decreases with age. Several studies have reported that although suicide mortality rates are high in older adults (Merrill and Owens, 1990; Ministry of Health and Welfare, 2023), suicide attempt rates are low (De Leo et al., 2005; Sendbuehler and Goldstein, 1977; Kim et al., 2024). Furthermore, although prior suicide attempts function as the most important variable in predicting (Bostwick et al., 2016; Lewinsohn et al., 1994; Malafosse, 2005), 70 % of all suicide deaths occur in people without a prior suicide attempt (Bommersbach et al., 2023), so this single variable alone is insufficient to predict suicide risk. In addition, anxiety (Beghi et al., 2013; Favril et al., 2022; Hawton et al., 2013; Scoliers et al., 2009; Sheikholeslami et al., 2008), stress (Kim et al., 2021; Shelef et al., 2018), alcohol consumption (Darvishi et al., 2015; Ledden et al., 2022) and impulsivity (Sastre-Buades et al., 2021), which were reported as suicide risk factors in previous studies, were also identified as major predictive factors in this study. The model was validated using a test cohort recruited separately from the training cohort. Most previous studies have performed training and validation within the same sample, whereas few studies have conducted external validation (Belsher et al., 2019). Previous studies conducted using internal validation had limited validation power because the validation was performed within the same sample, and external validation is known to be the best way to improve the generalizability of such models (Mansourian et al., 2021). In this study, the effect of overfitting was excluded using the same model in the two groups with heterogeneous trends collected over different periods, and suicide attempts could be predicted with acceptable accuracy.

Previous systematic reviews have shown that the accuracy, expressed as the AUC, in prediction models for suicide attempt risk based on cohort studies ranged from 0.71 to 0.93, and the PPV ranged from 0.001 0.35 (Belsher et al., 2019). Meanwhile, a previous study built a prediction model through survival analysis for a prospective cohort of high-risk suicide groups and verified its accuracy using the c-index. Internal validation was conducted by dividing the training data and validation data into 75 % and 25 %, respectively, and the c-index of the Cox model was between 0.692 and 0.779 (Wei et al., 2021). The accuracy of the model developed in this study was no better or worse than that of previous studies when internally verified, but the accuracy of external verification was lower than this; therefore, there may be difficulties in reliability when using it in actual clinical practice.

People currently taking psychiatric medications are at a higher risk of subsequent suicide attempts, as previously reported (Reneflot et al., 2019). However, in the long-term risk prediction model, it is noteworthy that the risk of suicide attempts was reported to be the highest in the group in which medication compliance was reported to be low at 25–50 % in the univariate analysis. In major mental illnesses such as schizophrenia and mood disorders, medication noncompliance has been repeatedly reported as a risk factor for suicide (Callor et al., 2005; Warriach et al., 2021; Weiss and Gorman, 2005). That is, if treatment is received irregularly despite the need for drug treatment, this may increase the risk of suicidal behavior, and appropriate drug treatment may have the potential to reduce the risk of suicidal behavior.

This K-COMPASS study is the first to prospectively analyze high-risk groups for suicide in South Korea and the second to construct a prediction model through survival analysis of a prospective cohort of high-risk groups for suicide and to verify the accuracy of the model through the c-index. Unlike previous studies, this study minimized selection bias by covering all urban and rural areas, hospitals, and communities in Korea, performed a structured psychiatric expert evaluation, and performed external validation together, unlike previous studies that mainly performed only internal validation, to verify accuracy more objectively. In addition, we constructed a model that can be applied to long-term risks as well as short- and medium-term risks as the model includes survival analysis to predict the long-term risk of suicide attempts, not just 3 months and 1 year.

This study had some limitations. First, because it was conducted in a specific population group in Korea, there may be limitations in generalizing the results to other countries or groups with different cultural backgrounds. Second, the data used in this study often depended on self-reports; therefore, the accuracy of the reported information may be limited, as self-reported data may be distorted by memory errors or social desirability biases. Third, although this study included psychiatric medication use as a variable, detailed information such as the exact dosage of medication use, duration of use, and medication change history was insufficient, limiting the ability to clearly identify the correlation between medication use and suicide attempts. Another potential limitation of this study is the presence of site-specific variations, which were not explicitly controlled for in the analyses. Finally, the high dropout rate during the follow-up observation may have resulted in selection bias, which may have overestimated or underestimated the risk of suicide attempts.

This study constructed a statistical model to predict the short-, mid-, and long-term risks of suicide attempts through a long-term prospective cohort analysis of high-risk patients in South Korea, one of the countries with the highest suicide risk in the world. The constructed suicide attempt risk prediction model showed acceptable accuracy in an independent test cohort; however, its accuracy decreased. Since it is difficult to predict the risk of suicide attempts in various population groups using a single model, future research is needed to develop additional risk prediction models for more detailed population groups such as adolescents, the elderly, and cancer patients. In addition, we plan to confirm objective information on drug use and suicide attempts by linking it with health insurance records or other real-world data and analyzing suicide attempts after dropping out.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT for the English translation of the manuscript, which was initially written in Korean. After using this tool, the manuscript underwent further language refinement through the professional English editing service, Editage. (https://www.editage.co.kr/) After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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CRediT authorship contribution statement

Shim Se-Hoon: Writing – review & editing, Data curation. **Moon Jung-Joon:** Writing – review & editing, Data curation. **Yang Jeong Hun:** Writing – original draft. **Cho Seong-Jin:** Writing – review & editing, Data curation. **Kang Ri-Ra:** Writing – review & editing, Formal analysis. **Kim Shin Gyeom:** Writing – review & editing, Data curation. **Kang Dae Hun:** Writing – review & editing, Methodology. **Lee KangYoon:** Writing – review & editing, Data curation. **Kim Min Ji:** Writing – review & editing, Validation. **Ahn Yong Min:** Writing – review & editing, Supervision. **Lee Sang Yeol:** Writing – review & editing, Data curation. **Yang Chan-Mo:** Writing – review & editing, Data curation. **Kim Min-Hyuk:** Writing – review & editing, Data curation. **Kim Yong-gyom:** Writing – review & editing, Methodology, Conceptualization. **Lee Jinhee:** Writing – review & editing, Data curation. **Yoo Jieun:** Writing – review & editing, Resources, Methodology, Data curation. **Kang Won Sub:** Writing – review & editing, Data curation. **Park C. Hyung Keun:** Writing – review & editing, Formal analysis. **Lee Weon-Young:** Writing – review & editing, Resources, Data curation. **Rhee Sang Jin:** Writing – review & editing, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ajp.2025.104407.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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