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한국 청소년의 비만 위험 예측 노모그램 개발 : 2024년 청소년건강행태조사 자료를 이용한 이차 분석

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Nomogram for Predicting the Risk of Obesity in Korean Adolescents : Secondary Analysis of the 2024 Korea Youth Risk Behavior Survey

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Abstract

Purpose : This study aimed to identify sociodemographic, behavioral, psychosocial, and digital health determinants of obesity among Korean adolescents and to develop an individualized obesity risk prediction model, using recent nationally representative data. **Methods :** Data were obtained from the 2024 Korea Youth Risk Behavior Web-based Survey, in which 49,996 middle- and high-school students participated. Complex sample logistic regression was used to identify factors associated with obesity, after accounting for survey weights and sampling design. A nomogram was constructed, based on the final multivariable model to estimate individual obesity risk. Model performance was evaluated using discrimination and calibration analyses, with internal bootstrap validation and decision curve analysis. **Results :** Male gender, lower academic performance, lower economic status, poorer subjective health status, fewer days of muscle-strengthening exercise, high-risk smartphone use, and older age were significantly associated with higher obesity risk. The prediction model demonstrated modest discrimination, with an area of 0.64 under the receiver operating characteristic curve and showed an acceptable level of calibration between predicted and observed probabilities. Furthermore, DCA confirmed that the nomogram provides a superior net clinical benefit for targeted interventions. The nomogram enabled intuitive visualization of individual risk profiles. **Conclusion :** This study presents a practical obesity risk prediction model and nomogram for Korean adolescents, based on recent national data. Despite modest predictive performance, the tool may support early screening and targeted prevention strategies in school and public health settings. Future research incorporating objective measurements and longitudinal data may further improve predictive accuracy.

Key words : Obesity, Adolescent, Risk factors, Health behavior, Nomograms

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Ⅰ. Introduction

The prevalence of adolescent obesity in Korea has continued to rise over the past decade, reflecting rapid societal and behavioral transitions among youth. Global trends similarly indicate growing burdens of childhood and adolescent obesity, driven by changes in diet, sedentary lifestyles, and environmental influences [1]. Prolonged academic demands reduced physical activity, and increased screen exposure have further contributed to energy imbalance among Korean adolescents [2]. The COVID-19 pandemic intensified these patterns by limiting outdoor activity and expanding screen-based learning, reinforcing behaviors linked to excess weight gain [3].

Although prior studies have identified factors associated with adolescent obesity in Korea, many relied on pre-pandemic datasets [4] and did not capture the substantial shifts in technology use, daily routines, and perceived well-being that now characterize adolescent lifestyles. Additionally, earlier work often examined individual determinants in isolation rather than integrating sociodemographic, psychosocial, behavioral, and digital factors within a comprehensive framework [5].

The Korea Youth Risk Behavior Web-based Survey (KYRBS) provides nationally representative and annually updated surveillance data on adolescent health behaviors. However, the 2024 KYRBS dataset—reflecting post-pandemic changes in smartphone dependence, subjective health perception, and physical activity—has not yet been fully utilized for obesity risk prediction. Nomograms offer a clinically intuitive method for translating multivariable models into individualized risk estimates and have been widely applied across medical and public health fields [6,7]. Compared to conventional logistic regression reporting, which primarily focuses on population-level associations, or "black-box" machine learning models that lack interpretability, a nomogram provides an individualized risk estimate while maintaining high transparency. This format is optimally aligned with the study's goal of supporting frontline practitioners, such as school nurses, as it enables rapid, point-of-care risk stratification and effective risk communication without the need for advanced computational software. Despite their utility, no studies have developed a nomogram-based prediction model for adolescent obesity using the most recent KYRBS data. Despite their utility, no studies have developed a nomogram-based prediction model for adolescent obesity using the most recent KYRBS data.

Adolescent obesity is increasingly recognized as a multifactorial condition influenced by the interaction of individual behaviors, psychosocial well-being, family context, and rapidly evolving digital environments. In Korea, competitive educational environments and extended sedentary study coexist with high smartphone penetration, creating a unique risk context distinct from that of Western countries.

Digital behaviors, including excessive smartphone use, have emerged as novel obesity-related exposures. Prior studies have linked prolonged screen time to reduced physical activity, sleep disruption, and altered eating behaviors, all of which contribute to adiposity accumulation [8,9]. However, most earlier investigations examined screen exposure as a single behavioral variable, without integrating it into multivariable risk prediction frameworks alongside socioeconomic and psychosocial factors. As adolescent lifestyles continue to digitalize, predictive models that fail to account for such factors may underestimate real-world obesity risk.

Therefore, this study aimed to (1) identify predictors of obesity among Korean adolescents using 2024 KYRBS data and (2) construct an individualized nomogram incorporating sociodemographic, behavioral, psychosocial, and digital indicators. These findings provide updated evidence to support early identification and targeted obesity-prevention strategies in school and public health settings.

Ⅱ. Methods

1. Study Design

This cross-sectional study used data from the 2024 Korea Youth Risk Behavior Web-based Survey (KYRBS), an annual national surveillance system administered by the Korea Disease Control and Prevention Agency. KYRBS is a nationally representative, school-based survey that employs a complex, multistage sampling design with stratification, clustering, and sampling weights to produce population-level estimates of adolescent health behaviors in Korea [10].

2. Participants

Participants included middle- and high-school students who completed the 2024 KYRBS. Among the initial 52,898 participants, cases with incomplete anthropometric data or missing values for key behavioral or psychosocial variables were excluded. Specifically, 2,152 cases were excluded due to incomplete anthropometric data (height or weight), and 750 cases were removed for missing values in behavioral or psychosocial variables. After applying these exclusion criteria, a total of 49,996 adolescents were included in the final analytic sample.

3. Measures

1) Outcome Variable

Obesity was defined as a body mass index at or above the sex- and age-specific 95th percentile based on the 2017 Korean National Growth Chart, which is the recommended clinical reference for Korean children and adolescents [11,12].

2) Independent Variables

Independent variables included sociodemographic, behavioral, psychosocial, and digital factors. Sociodemographic variables were gender, age (year), academic performance (high, average, low), and economic status (high, middle, low), which have been consistently reported as predictors of adolescent obesity [13-15]. Behavioral factors were assessed using the number of strength training days per week, reflecting muscle-strengthening activity during the previous 7 days. Subjective health status was measured using a single-term self-rated health question (good, moderate, bad), which is widely used as an indicator of overall physical and mental health [16]. Digital behavior was captured using the KYRBS high-risk smartphone use classification (low risk, moderate risk, high risk), based on evidence linking excessive smartphone use to physical inactivity, sleep disruption, and weight gain [8]. Psychosocial status was evaluated using the Generalized Anxiety Disorder-7 (GAD-7) and categorized as anxiety present vs. absent according to the study's operational definition [17].

4. Statistical Analysis

Statistical analyses were performed using SPSS 26.0 and R 4.2.2, specifically utilizing the rms, survey, pROC, and dcurves packages for model development validation, and decision curve analysis. All analyses accounted for KYRBS sampling weights, stratification, and primary sampling units to ensure valid population estimates. Descriptive statistics characterize obesity as prevalence across participant subgroups. To ensure the reproducibility of the variable selection process, a systematic two-step approach was employed. First, univariate analyses (Rao-Scott chi-square tests and unadjusted complex-sample simple logistic regressions) were conducted to evaluate the association between each candidate variable and obesity. Variables demonstrating a statistical significance of $p < .05$ in the univariate screening were sub-

Table 1. General Characteristics of Adolescents by Obesity Status (N = 49,996)

	Characteristics	Categories	Normal (n=43,580)		Obesity (n=6,416)		t or F§ (*p*)
			n†	%‡	n†	%‡	
			or M±SE		or M±SE		
Sociodemo-graphic	Age(year)		14.93±0.03		15.24±0.33		96.68(<.001)
	Gender	Male	21,336	49.0	4,047	63.7	289.19
		Female	22,244	51.0	2,369	36.3	(<.001)
	Academic performance	High	17,079	39.2	2,064	31.7	100.57
		Average	12,850	29.5	1,798	27.9	(<.001)
		Low	13,651	31.3	2,554	40.4	
	Economic status	High	18,593	43.5	2,472	39.0	50.67
		Middle	20,487	46.6	3,038	47.1	(<.001)
		Low	4,500	9.9	906	13.9	
	Subjective health status	Good	29,842	68.3	3,518	54.2	236.92
		Moderate	10,221	23.5	1,924	30.7	(<.001)
		Bad	3,517	8.2	947	15.1	
Behavioral	Weekly breakfast frequency		3.57±0.02		3.35±0.04		33.28(<.001)
	Nutrition education school	No	20,100	46.9	3,009	47.8	1.38(.240)
		Yes	23,480	53.1	3,407	52.2	
	Physical activity 60min (days past week)		2.22±0.02		2.25±0.31		0.86(.354)
	Vigorous physical activity (days past week)		2.38±0.02		2.40±0.30		0.52(.471)
	Muscle strengthening exercise (days past week)		1.46±0.02		1.35±0.03		13.09(<.001)
	Average sitting time per (days past week)		10.50±0.03		10.57±0.06		1.41(.236)
	Sleep recovery sufficiency	Sufficient	9,647	21.5	1,491	22.6	2.04
		Neutral	13,171	30.0	1,950	30.1	(.131)
		Insufficient	20,762	48.4	2,975	47.3	
Psycho-social	Sadness	No	31,630	72.7	4,687	73.1	0.57
		Yes	11,950	27.3	1,729	26.9	(.450)
	Loneliness	Rarely	19,265	44.0	2,876	44.0	1.23
		Sometimes	16,260	37.4	2,328	36.5	(.293)
		Often	8,055	18.7	1,212	19.5	
	Anxiety	Normal	37,663	86.3	5,441	84.5	13.08
		Anxious	5,917	13.7	975	15.5	(<.001)
	Alcohol consumption	Non-drinker	39,712	91.0	5,670	88.2	
		Low frequency	3,563	8.3	681	10.8	16.15
		Moderate frequency	205	0.5	53	0.8	(<.001)
		High frequency	100	0.2	12	0.2	
	Smoking	Non-smoker	41,889	96.0	6,137	95.6	
		Low frequency	586	1.3	101	1.6	1.05
		Moderate frequency	187	0.4	30	0.5	(.369)
		High frequency	918	2.2	148	2.3	
	Intentional drug use	No	43,076	98.8	6,343	98.8	0.11
		Yes	504	1.2	73	1.2	(.740)
Digital health	Smartphone use	Low risk	4,140	9.7	484	7.6	28.19
		Moderate risk	14,889	34.4	1,941	30.7	(<.001)
		High risk	24,551	55.9	3,991	61.8	

*: unweighted count; †: weighted %; ‡Rao-Scott test
SE = Standard Error

sequently selected for inclusion in the final multivariable complex-sample logistic regression model to adjust for potential confounders. Adjusted odds ratios (ORs) and 95% confidence intervals (CIs) for predictors of obesity, with $p < .05$ considered statistically significant.

A nomogram was constructed using coefficients from the final multivariable model. Model discrimination was evaluated using the area under the receiver operating characteristic curve (AUC), and calibration was examined by plotting predicted versus observed obesity probabilities. Internal validation was conducted using 1,000 bootstrap resamples to quantify model optimism and calculate the optimism-corrected area under the ROC curve (AUC) and calibration slope. Furthermore, to evaluate model stability and the potential risk of overfitting, the Events Per Variable (EPV) ratio was calculated. Finally, decision curve analysis (DCA) was performed to evaluate the clinical utility of the nomogram by estimating the net benefit across a range of threshold probabilities compared to “treat-all” and “treat-none” strategies.

5. Ethical Considerations

This study was exempted from review by JBNU IRB (JBNU-2025-06-044).

Ⅲ. Results

1. General Characteristics of Participants

Among the 49,996 adolescents included in the analysis, 12.8% (n=6,416) met the criteria for obesity. Within the obesity group, the proportion of male students 63.7% (n=4,047) was higher than that of female students 36.3% (n=2,369). Regarding academic performance, the obesity group was distributed among low 40.4% (n=2,554), high 31.7% (n=2,064), and average 27.9% (n=1,798) categories. In terms of economic status, adolescents in the middle 47.1% (n=3,038) and high 39.0% (n=2,472) categories represented the majority of the obesity group, while the low category accounted for 13.9% (n=906). For subjective health status, the proportions of those perceiving their health as good, moderate, and bad were 54.2% (n=3,518), 30.7% (n=1,924), and 15.1% (n=947), respectively. Additionally, the obesity group included those engaging in fewer muscle-strengthening sessions and those categorized as high-risk smartphone users 61.8% (n=3,991). Detailed characteristics by obesity status are presented in Table 1.

2. Factors Associated with Obesity

The multivariable logistic regression model revealed several significant predictors. Male gender substantially increased the likelihood of obesity (OR=2.17, 95% CI=2.02−2.34). Academic performance showed a graded association; students with high (OR=0.72, 95% CI=0.67−0.78) or average performance (OR=0.81, 95% CI=0.75−0.87) exhibited lower odds relative to those with low performance. Economic status demonstrated a similar pattern, with high-SES (OR=0.85, 95% CI=0.77−0.93) and middle-SES adolescents (OR=0.83, 95% CI=0.77−0.91) experiencing lower risk than those from low-SES households.

Subjective health status emerged as one of the strongest predictors; adolescents rating their health as good (OR=0.46, 95% CI=0.42−0.51) or moderate (OR=0.76, 95% CI=0.69−0.84) had markedly lower odds. Anxiety symptoms were not significantly associated (OR=0.99, 95% CI=0.91−1.08). High-risk smartphone use was associated with greater obesity risk (OR=1.28, 95% CI=1.13−1.44). Age was positively associated with obesity (OR=1.07, 95% CI=1.05−1.09). Among behavioral factors, muscle strengthening exercise days past week demonstrated a protective association (OR=0.93,

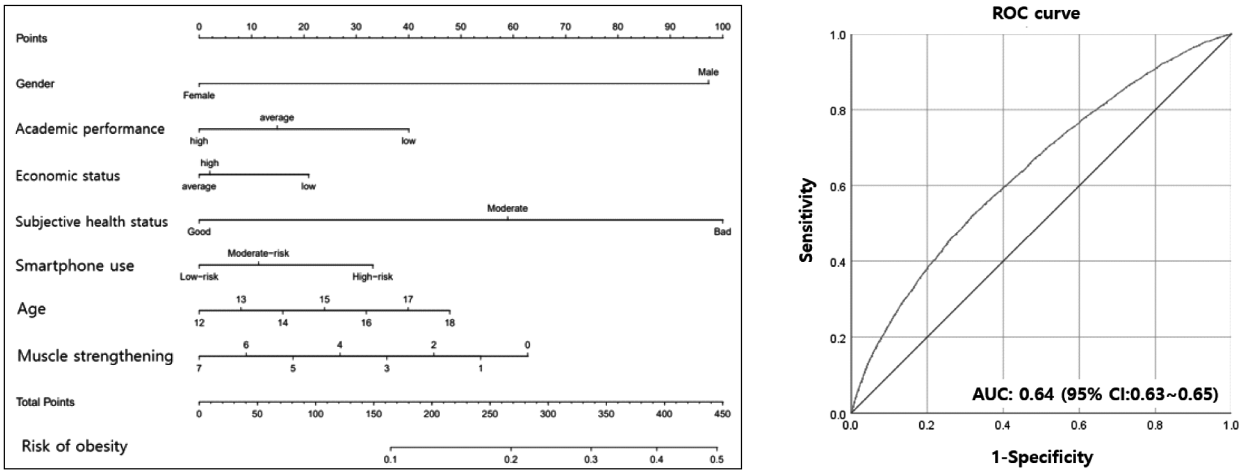
Table 2. Multivariable Logistic Regression Predicting Obesity Among Adolescents

Characteristics	Categories	B	SE	*p*	OR	95% CI		VIF
						Lower	Upper	
Gender	Male	0.78	0.04	<.001	2.17	2.02	2.34	1.17
	Female				1			
Academic performance	high	-0.33	0.04	<.001	0.72	0.67	0.78	1.16
	average	-0.21	0.04	<.001	0.81	0.75	0.87	
	low				1			
Economic status	high	-0.17	0.05	<.001	0.85	0.77	0.93	1.11
	middle	-0.18	0.04	<.001	0.83	0.77	0.91	
	low				1			
Subjective health status	Good	-0.77	0.05	<.001	0.46	0.42	0.51	1.11
	Moderate	-0.27	0.05	<.001	0.76	0.69	0.84	
	bad				1			
Anxiety	Anxious	-0.01	0.04	.875	0.99	0.91	1.08	1.08
	Normal				1			
Alcohol consumption	High frequency	-0.28	0.33	.404	0.76	0.40	1.45	1.06
	Moderate frequency	0.24	0.18	.170	1.27	0.90	1.80	
	Low frequency	0.06	0.05	.268	1.06	0.96	1.17	
	Non-drinker				1			
Smartphone use	High risk	0.25	0.06	<.001	1.28	1.13	1.44	1.11
	Moderate risk	0.10	0.06	.108	1.11	0.98	1.26	
	Low risk				1			
Age(year)		0.06	0.01	<.001	1.07	1.05	1.09	1.07
Breakfast days (per week)		-0.01	0.01	.072	0.99	0.98	1.00	1.06
Muscle strengthening exercise (days past week)		-0.07	0.01	<.001	0.93	0.92	0.95	1.17

95% CI=0.92–0.95). Table 2 summarizes the regression results.

3. Model Performance and Nomogram Construction

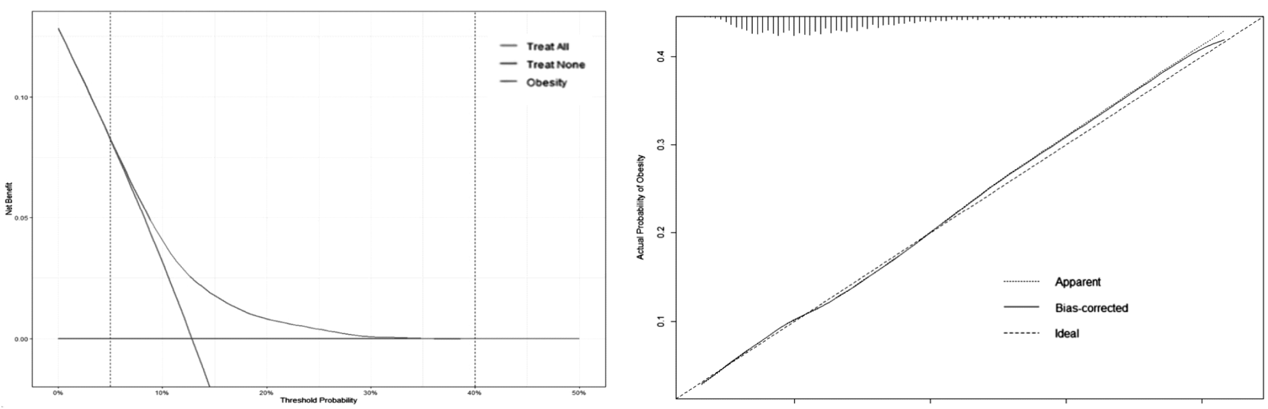
The prediction model demonstrated modest discrimination with an apparent AUC of 0.64. After 1,000 bootstrap resamplings, the optimism-corrected AUC remained robust at 0.64, and the calibration slope was 0.994, indicating minimal optimism bias. To visually assess the model's reliability, a calibration plot was generated using 1,000 bootstrap resamples. The bias-corrected curve demonstrated near-perfect alignment with the ideal 45-degree diagonal line, confirming that the predicted probabilities were highly consistent with the actual observed obesity rates. This indicates that the model is well-calibrated and provides accurate risk estimates across the entire probability range. Regarding model stability, the model included 6,416 obesity events and 16 predictor parameters (including dummy variables), yielding an Events Per Variable (EPV) ratio of 401. This vastly exceeds the recommended threshold of 10, confirming a negligible risk of overfitting and ensuring high model stability. To optimize model parsimony and enhance clinical utility, the final nomogram was constructed by focusing on variables with significant predictive weight. While ten variables were initially evaluated in the multivariable model (Table 2),



A. Nomogram for predicting individual obesity risk

B. ROC curve of the prediction model

Figure 1. Nomogram and ROC curve for adolescent obesity prediction: (A) Nomogram for predicting individual obesity risk; (B) Receiver operating characteristic curve for model validation.



A. Decision Curve Analysis for Obesity Prediction Model

B. Calibration Plot for the Obesity Prediction Nomogram

Figure 2. Internal validation and clinical utility of the obesity prediction nomogram: (A) Decision curve analysis; (B) Calibration plot.

non-significant factors with negligible point contributions—specifically anxiety, alcohol use, and breakfast consumption—were excluded to provide a more streamlined and interpretable interface for frontline health practitioners. Accordingly, A nomogram was developed to facilitate individualized obesity-risk estimation, with gender and subjective health contributing the highest point values, followed by academic performance, muscle-strengthening frequency, and smartphone use. Furthermore, Decision Curve Analysis (DCA) was conducted to evaluate the clinical utility of the obesity prediction nomogram. Within the threshold probability range of 5% to approximately 35%, the prediction model demonstrated a higher net benefit compared to both the "treat-all" and "treat-none" strategies. This indicates that using the developed nomogram to identify adolescents at high risk for obesity provides a superior net clinical benefit for targeted interventions over default strategies (Figures 1,2).

Ⅳ. Discussion

This study developed an adolescent obesity risk prediction model and nomogram using nationally representative 2024 KYRBS data, reflecting post-pandemic behavioral and digital environments. By integrating sociodemographic, behavioral, psychosocial, and digital factors, the model provides updated evidence on obesity determinants among Korean adolescents and offers a practical tool for early risk stratification in public health settings.

These findings are broadly consistent with previous studies using earlier waves of the Korea Youth Risk Behavior Web-based Survey, which identified sex, academic performance, socioeconomic status, and physical inactivity as key correlates of adolescent obesity [4,5]. However, most prior Korean studies focused on association analyses rather than integrated risk prediction frameworks and relied on pre-pandemic data [4].

A previous nomogram-based study using the 2020 KYRBS reported moderate predictive performance and highlighted traditional behavioral factors such as physical activity and sedentary time [18]. In contrast, the present study leveraged more recent 2024 data and incorporated high-risk smartphone use as a core predictor, reflecting post-pandemic digital behavioral shifts. The inclusion of this variable represents an important advancement, as digital exposure has become a defining feature of contemporary adolescent lifestyles in Korea [8,19]. Together, these differences suggest that obesity risk prediction models must be periodically updated to remain responsive to evolving behavioral environments.

Consistent with prior international and regional studies, male adolescents demonstrated substantially higher obesity risk than females [1,20]. This disparity may be explained by gender-specific behavioral patterns, including higher caloric intake, lower dietary quality, and greater engagement in sedentary screen-based leisure among boys [2,21]. In addition, sociocultural norms in East Asian contexts may differentially shape physical activity participation across genders during adolescence [22,23], reinforcing cumulative risk trajectories. These findings underscore the importance of gender-sensitive obesity prevention strategies rather than uniform interventions.

Socioeconomic status and academic performance remained independently associated with obesity risk after adjustment for behavioral factors, highlighting the structural nature of adolescent obesity [13-15]. Adolescents from socioeconomically disadvantaged backgrounds may experience constrained access to healthy environments, reduced opportunities for organized physical activity, and heightened exposure to chronic stress [14,15]. Such conditions interact synergistically with academic pressure, sleep insufficiency, and unhealthy coping behaviors. The observed academic gradient further suggests that obesity risk is embedded within broader educational and psychosocial contexts, supporting school-based interventions that integrate academic support with health promotion.

Subjective health status emerged as one of the most influential predictors in the model. Subjective health status is increasingly recognized as a robust, integrative indicator encompassing physical symptoms, emotional well-being, sleep quality, and functional capacity [16]. Adolescents perceiving their health as bad may already experience early metabolic dysregulation or psychosocial distress that predisposes them to weight gain [21].

Among behavioral factors, muscle-strengthening exercise demonstrated a protective association with obesity independent of other activities. Resistance-based physical activity contributes to favorable body composition, insulin sensitivity, and metabolic regulation during adolescence [2,20]. Importantly, such activities may be more feasible within time-constrained academic schedules than prolonged aerobic exercise, making them a realistic intervention target in highly competitive educational environments such as Korea.

Digital health represents a defining feature of contemporary adolescent lifestyles and a key contribution of this study. High risk smartphone use was independently associated with increased obesity risk, aligning with growing evidence linking excessive screen exposure to reduced physical activity, sleep disruption, and dysregulated eating patterns [9,10,18]. In societies with near-universal smartphone access, digital health may function as upstream determinants that indirectly amplify traditional obesity risk factors. These findings emphasize that effective adolescent obesity prevention must extend beyond diet and physical activity to incorporate digital health literacy and responsible technology use.

The nomogram developed in this study translates these multidimensional risk factors into an individualized and visually interpretable tool. Although the model demonstrated modest discrimination (AUC = 0.64), such performance is comparable to other population-based obesity prediction models relying on self-reported data [18]. For instance, a previous nomogram-based prediction model utilizing the same KYRBS dataset reported an AUC of 0.68 [18], demonstrating that predictive performance in the 0.60 – 0.70 range is a common methodological threshold when relying on large-scale self-reported adolescent health surveys. Furthermore, it is important to distinguish between clinical prediction models and population-based screening tools. While clinical models utilizing objective blood biomarkers to predict metabolic risks naturally achieve higher discrimination (AUC = 0.80) [20], models relying exclusively on non-invasive, self-reported surveillance data face a natural performance ceiling. Therefore, the AUC of 0.64 achieved in our study reflects the inherent methodological constraints of large-scale survey data, proving that our nomogram is highly robust and practically acceptable as a large-scale screening tool in school health settings. This clinical utility was further confirmed by our Decision Curve Analysis (DCA). Within the threshold probability range of 5% to approximately 35%, the prediction model demonstrated a higher net benefit compared to both the “treat-all” and “treat-none” strategies. In resource-limited school and community settings, even moderate discrimination can be meaningful when applied to large populations, as it allows school nurses and public health practitioners to efficiently allocate preventive resources to those who will benefit most.

From a public health and policy perspective, the findings underscore the potential value of integrating multivariable risk prediction tools into school-based health programs [6,7]. Adolescence is a critical period during which obesity trajectories are established and often persist in adulthood [1,20], and early identification of high-risk individuals allows for timely, targeted interventions. The nomogram developed in this study supports a holistic assessment by incorporating modifiable behaviors (e.g., muscle-strengthening activity and smartphone use) alongside structural determinants such as socioeconomic disadvantage and academic context. This approach aligns with contemporary frameworks emphasizing precision prevention – tailoring intervention intensity and content according to individual risk profiles rather than applying uniform strategies across populations. Importantly, the transparent scoring structure enables use by school nurses and community health practitioners without advanced statistical training. In resource-limited settings, the tool may support prioritization for counseling, physical activity promotion, digital health education, or referral to supportive services.

Several limitations warrant consideration. Anthropometric measures were self-reported, potentially underestimating obesity prevalence [12]. Dietary intake, objective physical activity, and environmental factors were not available in the KYRBS dataset, and the cross-sectional design precludes causal inference. Nonetheless, the use of recent nationally representative data and the inclusion of digital health indicators enhance the relevance of the findings to current adolescent health challenges.

In conclusion, this study provides updated evidence on the multifactorial determinants of adolescent obesity in Korea and presents a practical nomogram applicable to school and public health contexts. The findings support a comprehensive prevention approach that integrates socioeconomic context, academic environment, physical activity promotion, and digital health management. While the model's discrimination reflects the natural limits of self-reported survey data, the nomogram and its validated clinical net benefit offer a highly practical, easily interpretable tool for school and public health practitioners to support early screening. Future longitudinal studies incorporating objective behavioral and environmental measures are needed to refine predictive accuracy and to evaluate the real-world effectiveness of nomogram-guided interventions.

Ⅴ. Conclusion

Using nationally representative 2024 KYRBS data, this study developed a multivariable obesity risk prediction model and nomogram incorporating sociodemographic, behavioral, and digital health factors. The identification of key predictors—including male gender, socioeconomic disadvantage, lower academic performance, poor subjective health status, high-risk smartphone use, and low engagement in muscle-strengthening activities—highlights the complex, multidimensional nature of adolescent obesity in the post-pandemic era. While the model's discrimination was modest, the developed nomogram offers a practical, easily interpretable tool that allows school and public health practitioners to perform efficient early screening and risk stratification. Moving forward, integrating objective anthropometric measures and longitudinal data into this framework will be essential to further enhance predictive performance and maximize the model's utility for targeted adolescent health promotion.

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