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Article

Conceptually Informed AI/ML for South Korean Adolescent Smartphone Overdependency: Low-Risk Screening, Construct Exploration, & Place-Based Policy Implication Profiles

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Abstract

Smartphone overdependence among South Korean adolescents, affecting nearly 40%, poses a growing public health concern, with usage patterns varying by regional context. Leveraging conceptually informed AI/ML models, this study (1) develops a high-performing, low-risk screening tool to monitor disease burden, (2) leverages AI/ML to explore psychologically meaningful constructs, and (3) provides place-based policy implication profiles to inform public health policy. Using data from 1,873 adolescents in the 2023 Smartphone Overdependence Survey, we conceptually selected 131 features across 12 identified constructs. A nested modeling approach identified a low-risk screening tool using 59 features that achieved strong predictive accuracy (AUC = 81.5%), with smartphone use case features contributing approximately 20% to performance. Construct-specific models confirmed the importance of Smartphone Use Cases, Perceived Digital Competence & Risk, and Consequences & Dependence (AUC range: 80.6%–89.1%) and uncovered cognitive patterns warranting further study. Place-stratified analysis revealed substantial regional variation in model performance (AUC range: 71.4%–91.1%) and distinct local feature effects. Overall, this study demonstrated the value of integrating conceptual frameworks with AI/ML to detect adolescent smartphone overdependence, offering novel approaches to monitoring disease burden, advancing construct-level insights, and providing targeted, place-based public health policy recommendations within the South Korean context.

Keywords: smartphone overdependence; adolescents; conceptually informed modeling; Artificial Intelligence (AI); Machine Learning (ML); low-risk screening tools; construct-level analysis; Explainable AI (XAI); urbanicity / place-based analysis; South Korea

1. Introduction

Smartphone overdependency among adolescents in South Korea has become a critical public health issue, with over 98% of youth owning smartphones and engaging in unprecedented screen time levels [1]. The prevalence rate among Korean adolescents, ranging from 37% to 40%, is the highest among all age groups [2,3]. This raises concerns due to its strong associations with mental health issues, negative emotions, suicidal ideation, and substance use [4–6]. Excessive smartphone use is linked to psychological problems such as depression, anxiety, OCD, and ADHD, as well as elevated stress and loneliness [7]. Furthermore, a recent meta-analysis found that smartphone overdependence negatively affects academic achievement among adolescents and young adults [8].

In response, policies have emphasized early identification and intervention, with schools playing a central role in risk assessment [9]. These policies reflect global trends recognizing the impact of smartphones on educational settings. For instance, in France, using a smartphone in class is prohibited for students who are under 15 years old [10]. In the United States, at least 18 states have enacted laws or policies banning or restricting student smartphone use during the school day in K–12 settings [11]. In Korea, schools utilize structured self-report screening tools to classify students by risk level and deliver interventions, including psychological counseling, parental education, and behavioral therapy. These efforts reflect a coordinated public health strategy that integrates educational institutions, mental health services, and family support systems to address youth risk in a comprehensive manner. However, this traditional approach relies heavily on lengthy structured self-report surveys, requiring multiple reporters and asking psychologically intrusive items to determine intervention needs. These embedded survey concerns have been discussed in a large body of research.

First, the reliance on invasive psychological questions that probe deeply into adolescents' emotional and private experiences can be problematic. Items commonly ask whether students feel hopeless without their phones, experience declines in academic performance, or feel depressed after extended smartphone use [3]. While these items aim to identify risk, their intrusive nature, particularly those involving hopelessness or depressive symptoms, may raise ethical concerns when used at scale in educational settings. Such invasiveness may be particularly distressing for adolescents, who may have a more limited capacity to tolerate the emotional stress associated with self-reflection on sensitive topics compared to adults. As a result, questions that may appear relatively benign to adults can feel psychologically intrusive to adolescents, potentially triggering anxiety, embarrassment, or emotional discomfort. According to the literature, intrusive surveys are associated with increased response bias, reduced accuracy, and, in some cases, participant disengagement [12], particularly among youth concerned about privacy or stigma [13,14]. According to major ethical guidelines such as the Belmont Report, researchers are obligated to respect the dignity and welfare of participants and adhere to the principle of beneficence, which emphasizes "doing no harm, maximizing possible benefits, and minimizing potential risks" [15]. Similarly, Standard 3.04 of the APA Code of Ethics [16] states that psychologists must avoid causing harm to research participants and minimize unavoidable potential harm. Hasking et al. [17] found that 15% of adolescents with poorer psychological functioning than their peers reported feeling upset during survey completion, and experienced a decline in psychosocial functioning afterward. This suggests that particular attention must be paid to the potential for emotional distress among at-risk youth in their smartphone related problems when designing and administering surveys.

Given these concerns, predictive modeling using artificial intelligence and machine learning (AI/ML) has recently gained attention as a promising alternative. AI/ML technologies are already well-established across various domains for enabling precise classification and prediction [18]. In the context of public health and mental health, they are increasingly recognized for their potential to serve as efficient and sensitive screening tools [19]. Unlike traditional approaches that rely on lengthy and often intrusive questionnaires, AI/ML models can identify high-risk individuals with high performance and potentially reduce the number of indicators needed. Kim et al. [20] reported a precision of 87.60% when predicting adolescent smartphone overdependence from full-length surveys across five years of data, while Lee and Kim [21] used a small set of loggable smartphone-related variables yielding high performance when stratifying by age groups between 3 to 69 years old. International studies further validate this approach, showing that models built on psychological and demographic variables can accurately predict smartphone overdependency, offering alternatives to conventional assessments [22,23]. However, to the best of our knowledge, no prior study has developed a low-dimensional (i.e., minimal input) AI/ML model to predict smartphone overdependence specifically among adolescents. Furthermore, no existing models have explicitly utilized conceptually informed feature selection or been designed with the goal of minimizing psychological discomfort and ethical risk in assessment.

A second concern in current assessments is the insufficient attention to contextual factors such as region or urbanicity, despite emerging evidence that this context significantly shapes smartphone usage patterns. For instance, Sapienza et al. [24] explored the impact of urbanicity on smartphone use among approximately 500,000 users across 22 countries. The result shows that urban residents spend more time on their smartphones overall compared to rural users. Specifically, rural users dedicate proportionally more time to entertainment activities like gaming and social media, while urban users favor utility applications such as navigation, business, and productivity tools. The researchers suggest these patterns reflect environmental differences where rural users may turn to smartphones for entertainment due to limited physical recreation options, while urban users employ them as tools to navigate complex city environments. A study in Bangladesh shows that the overall prevalence of smartphone addiction is higher among preschoolers in urban areas than rural ones. One of the characteristics of urbanicity, high population density, has been shown to influence smartphone addiction among Koreans [25]. On the other hand, research in China found that adolescents in rural areas showed higher levels of smartphone addiction compared to their urban counterparts, driven by heightened feelings of loneliness and anxiety when not using smartphones [26,27]. These differences suggest that the relationship between adolescents' smartphone use and risk for overdependency may vary depending on urbanicity and regional contexts. Nevertheless, to our knowledge, no AI/ML-based models in smartphone overdependency are developed or evaluated with sufficient attention to urbanicity and regional contexts. This limits their ability to deliver place-sensitive predictions and policy implications.

Given these gaps, researchers have called for a shift toward predictive models that are not only accurate but are also ethically informed and sensitive to local variation. Such models should incorporate minimal yet high-yield features, reducing respondent burden while maintaining predictive power. Specifically, these predictors should strategically combine indicators and non-intrusive data to enhance predictive efficiency and ethical soundness. In addition, conceptually chosen predictors are crucial to not only improve interpretability but also ensure generalizability across different populations [28]. Additionally, carefully selected predictors reduce computational costs and data collection burdens, facilitating more sustainable and accessible implementations of predictive tools in real-world settings [29]. By combining these techniques with place-stratified eXplainability [30,31] evaluations, AI/ML-based models can effectively address public health imperatives to deliver tailored interventions while minimizing risk and burden.

1.1. Research Aims & Contributions

This study aims to advance the understanding, detection, and policy implications of adolescent smartphone overdependence in South Korea through the integration of conceptual frameworks and AI/ML methods. Grounded in public health and social sciences, we outline three aims:

1. Develop a high-performing, low-risk screening tool to detect adolescents at risk for smartphone overdependence using conceptually informed AI/ML modeling;
2. Leverage AI/ML toward construct exploration of contributing factors; and
3. Provide place-based policy profiles that offer insights into local variation in risk factors and model performance, enabling targeted intervention.

The study contributes methodologically by introducing a framework that prioritizes conceptually meaningful constructs over purely data-driven feature sets. Practically, it informs the design of adolescent-friendly screeners aligned with ethical research principles. Conceptually, it shows how AI/ML can illuminate patterns in adolescent behavior that align with psychologically meaningful constructs, offering new directions for behavioral research. From a policy perspective, it advances place-sensitive approaches to digital well-being, providing insights that can support regionally adaptive public health interventions.

2. Materials and Methods

The following sections outline our data, approach to feature selection and grouping, and analyses.

2.1. Data

Secondary data, collected by the National Information Society Agency (NISA) in South Korea, was used. The full sample consisted of 22,844 household members who had used a smartphone within the past month and were present and available for the interview, which took place from September to November 2023. During the interview, each participant was asked approximately 192 questions covering demographic characteristics, smartphone usage, online video services, counseling and education, awareness of overdependency, and psychosocial characteristics. In the current study, we focused on a total of 1,873 adolescent participants aged 10-18 from the full sample.

2.2. Outcome

The outcome variable in this study is smartphone overdependence. NISA measured this by administering the validated Smartphone Overdependence Scale [32]. This scale has ten questions measuring three facets: 1) the level of difficulty in controlling smartphone use, 2) concentration disruption due to smartphone use, and 3) the incidence of health, academic, or interpersonal conflicts caused by smartphone use. The scale uses a 4-point Likert ranging from Strongly disagree (1) to Strongly agree (4). Based on total scores, adolescents are categorized as high-risk (≥ 31 points), potential risk (23–30 points), or no risk (< 23 points). In our AI/ML models, we use the binary any-risk vs no-risk target as our label by combining the potential risk and high-risk groups. This is in line with our research aim to develop a low-risk screener for public health detection.

2.3. Conceptual Feature Selection & Construct Grouping

From the NISA survey, all individual items related to adolescents were considered candidates for inclusion. While the original NISA survey includes five broad domains (smartphone use, online video use, prevention and counseling, problem perception, and psychosocial characteristics), we regrouped items based on theoretical grounding. Two overarching domains (demographics and urbanicity) and ten theoretically grounded constructs were identified. Only items aligning with one of these domains or constructs were retained for analysis. This resulted in a total of 92 final items. After one-hot encoding, these 92 study items become 132 features.¹ In Appendix A, Tables A1 and A2 outline the 2 domains and 10 constructs, and their respective 132 features. Below, we define each construct and summarize its relevance to adolescent smartphone overdependence.

1. **Intent to Seek Smartphone Education.** This construct captures adolescents’ intention to engage in preventive education related to smartphone use [33]. Higher intention to seek education has been associated with reduced risk of overdependence.
2. **Preventive Education Experiences.** This reflects actual participation in educational or intervention programs designed to prevent smartphone addiction [34]. Although evidence for their effectiveness remains mixed, adolescents who have received such education often demonstrate greater awareness and are more likely to engage in help-seeking behaviors.
3. **Smartphone Use Cases.** This measures the frequency of engagement with different smartphone functions (e.g., gaming, video streaming, navigation) [35]. Entertainment and social networking applications, in particular, have been linked to increased overdependence due to their reward structures and habit-forming properties [36].
4. **Home Environment.** The home environment includes both physical and psychological aspects of the household context [37]. Prior studies have shown that conditions such as socioeconomic status, family structure, and parental support can shape adolescent behavior and potentially influence smartphone use [38,39].

¹ One dummy variable is dropped due to never being endorsed in the sample.

5. **Parental Prevention Efforts.** Parental prevention efforts refer to the strategies parents use to manage and guide their children's media use, including rule-setting, supervision, and open dialogue [40]. Active parental prevention efforts have been found to reduce risk for smartphone addiction, while overly restrictive or absent parenting may increase it [41,42].
6. **Social Support.** Social support refers to the perception that one is cared for, valued, and part of a network of mutual obligations [43]. Strong social support has been associated with reduced smartphone overdependence, potentially by mitigating negative emotions and enhancing self-regulation [44].
7. **Self-Regulation Assessments.** Self-regulation is the ability to control emotions, behaviors, and cognition in pursuit of long-term goals [45]. A growing body of research suggests that higher self-regulation is associated with lower levels of smartphone overdependence in adolescents [46].
8. **Perceived Digital Competence & Risk.** This construct refers to individuals' perceived abilities to effectively navigate digital environments (e.g., digital content creation, privacy awareness) as well as their perceived smartphone issues (e.g., excessive use, difficulty controlling short-form video consumption). These perceptions may shape how individuals engage with digital technology and manage potential overdependence [47].
9. **Life Satisfaction.** Life satisfaction refers to a person's evaluation of their overall well-being and quality of life [48]. Studies have shown that higher levels of smartphone addiction are correlated with lower life satisfaction among adolescents [49].
10. **Smartphone Consequences & Dependence.** Psychological distress is characterized by emotional suffering, typically involving symptoms of depression and anxiety [50]. Excessive smartphone use has been linked to increased psychological distress and related cognitive and neurological effects [7].

2.4. Artificial Intelligence/Machine Learning Models

This section describes our conceptual framework and development of AI/ML models, and then presents our evaluation methods. All analyses were conducted using Python version 3.10.13, with commonly used data science and machine learning libraries (e.g., scikit-learn, pandas, XGBoost, LightGBM). The codebase can be made available upon reasonable request to the corresponding author.

2.4.1. Conceptual Framework

We build various AI/ML models using two primary approaches: 1) nested modeling and 2) construct-based modeling. In the nested modeling, we begin with simple demographics and add sets of features one construct at a time. The sequence of nesting is based on the risk for psychological discomfort. In other words, we consider the ethical considerations with implementation-informed design. This conceptual approach was chosen to develop the low-risk screener. This would also identify the screener with the minimum features needed for high prediction accuracy. Next, we take a construct-based modeling approach to identify which construct feature sets have the most predictive power and examine the feature importance within. This provides a conceptual approach toward the construct exploration of contributing factors leveraging AI/ML.

2.4.2. AI/ML Classification Modeling

To examine smartphone overdependency among adolescents, we developed classification models to predict our binary outcome of any risk for adolescent smartphone overdependency. Here we discuss our data processing and AI/ML procedures.

Data Processing

Our dataset comprises of numerical and categorical variables. First, we one-hot encode the categorical variables in our dataset. To standardize our data, we then train a scalar on our training set using the StandardScalar function from the scikit-learn library [51]. This resulting scalar is then applied to the test set to prevent data leakage.

AI/ML Procedures

We applied widely used high-performing algorithms to maximize classification performance. They include logistic regression (LogReg), decision trees (DT), random forest (RF), extreme gradient boosting (XGBoost), multi-layer perceptron (MLP), and light gradient-boosting machine (LightGBM) [52–56]. We then split the data into an 80/20 training and out-of-sample test sets. The training set had 1,498 adolescents, and the test set had 375 adolescents, which were held constant across algorithms and all experiments. We use 5-fold cross-validation, nested within the training set, for hyperparameter tuning and out-of-sample testing for final performance evaluation. We tune hyperparameters specific to each algorithm using Optuna (an automatic hyperparameter optimization framework) with 50 iterations to minimize mean logarithmic loss across the 5-fold cross-validation (mean val loss) [57]. For MLP and gradient boosting algorithms, we utilize early stopping to prevent overfitting. We report the search spaces and hyperparameters for our reported models in Appendix B. In the final testing, model performance was assessed using three metrics: mean val loss, test loss, and the out-of-sample area under the receiver operating characteristic curve (AUC). The consistency between mean val loss and test loss was used to assess model generalizability, while the out-of-sample AUC was employed to evaluate the model's ability to discriminate between classes on unseen data [58,59].

2.4.3. eXplainable AI (XAI) Techniques

We apply XAI techniques to improve the interpretability of the model by identifying features that meaningfully contribute to its predictions [30,31]. This ensures transparency and interpretability of our classification models for predicting adolescent smartphone overdependency. We use two XAI tools, Shapley Additive exPlanations (SHAP) and Partial Dependence Plots (PDPs) [60,61].

SHAP assess both global (mean feature impact) and local (instance-specific) contributions of each predictor, clarifying how features influence predictions [61]. Additionally, we employed PDPs to analyze key nonlinearities, inflection points, and interaction thresholds in predictor-outcome relationships [62]. Section 3 presents SHAP beeswarm plots and PDPs to illustrate SHAP value distributions and the functional effects of high-impact predictors. We compute SHAP values to quantify and examine the rank and directionality of features, providing insights into how predictors influence predictions. We generate PDPs to visualize global marginal effects on the average prediction, providing insights into nonlinear relationships and slope inflection points.

2.4.4. Place-Stratified Predictive Analysis

We conduct a place-stratified predictive analysis by evaluating the performance of our AI/ML models on sample subsets stratified by urbanicity: 1) Metropolitan City, 2) Medium or Small City, and 3) Town or Rural District. Group comparisons found 31 significant differences by urbanicity out of 128 one-hot encoded features (Table 1). This may lead to nationally trained models missing key place-based nuances or inconsistent performance. Using our out-of-sample test set and stratifying the predictions by urbanicity, we recalculate the AUCs, SHAP, and PDPs only for those sample subsets and examine differences in feature importance and trends (see Tables A4–A6 in Appendix C for group comparisons across all study variables). We use these insights to provide place-based policy profiles in Section 4.1.

Table 1. Significantly Different Place-Stratified Features by Urbanicity (N = 1,873)

Construct	Variable	Metropolitan City (n=831)	Medium or Small City (n=714)	Town or Rural District (n=328)
Home Environment	House (n (%))*	167 (20.1%)	152 (21.3%)	90 (27.4%)
Smartphone Use Cases	Messenger (M (SD))***	5.31 (1.46)	5.41 (1.42)	5.02 (1.75)
	Scheduling (M (SD))**	2.06 (2.13)	1.86 (2.06)	1.62 (2.08)
	Health (M (SD))*	1.76 (2.04)	1.59 (1.91)	1.46 (1.98)
	Zoom Meetings (M (SD))*	0.73 (1.57)	0.54 (1.33)	0.59 (1.41)
	Investment (M (SD))***	0.86 (1.52)	0.63 (1.28)	0.62 (1.29)
	Watching Videos (M (SD))*	5.25 (1.62)	5.32 (1.58)	5.02 (1.81)
	Listening Music (M (SD))***	4.51 (1.97)	4.48 (2.04)	4.03 (2.35)
	Adult Content (M (SD))***	0.50 (1.15)	0.33 (0.94)	0.30 (0.94)
	Gambling (M (SD))***	0.48 (1.20)	0.29 (0.87)	0.32 (1.04)
	News (M (SD))**	2.57 (2.21)	2.30 (2.04)	2.16 (2.16)
	Educational Web Search (M (SD))**	4.06 (1.81)	3.84 (1.78)	3.64 (2.26)
	Navigation (M (SD))*	2.42 (1.92)	2.37 (1.95)	2.12 (2.00)
	Short Form YouTube (n (%))**	443 (53.3%)	315 (44.1%)	162 (49.4%)
	TikTok (n (%))*	145 (17.4%)	165 (23.1%)	68 (20.7%)
	Mostly Food (n (%))*	130 (15.6%)	80 (11.2%)	47 (14.3%)
Perceived Digital Competence & Risk	Gaming Side Effects (n (%))**	353 (42.5%)	313 (43.8%)	108 (32.9%)
	Issue Engagement (M (SD))*	2.80 (0.85)	2.70 (0.85)	2.81 (0.81)
	Content Creation (M (SD))*	2.49 (0.98)	2.43 (0.98)	2.62 (0.99)
	Privacy Awareness (M (SD))***	2.66 (0.88)	2.57 (0.86)	2.79 (0.86)
	Info for School/Work (M (SD))***	2.89 (0.87)	2.67 (0.94)	2.81 (0.92)
Consequences & Dependence	Low Battery Nervousness (M (SD))**	2.71 (0.83)	2.85 (0.86)	2.75 (0.85)
Parental Prevention	Teaches Use (n (%))**	397 (47.8%)	284 (39.8%)	130 (39.6%)
	Teaches Pros/Cons (n (%))*	514 (61.9%)	422 (59.1%)	176 (53.7%)
	Recommends Apps (n (%))***	396 (47.7%)	277 (38.8%)	152 (46.3%)
Social Support	Family Support (M (SD))**	3.29 (0.69)	3.17 (0.75)	3.26 (0.66)
	Friend Support (M (SD))*	3.13 (0.67)	3.07 (0.69)	3.17 (0.68)
	Fairness Perception (M (SD))***	2.93 (0.71)	2.81 (0.75)	3.03 (0.79)
Self-Regulation	Digital Detox (n (%))**	210 (25.3%)	153 (21.4%)	55 (16.8%)
	Designated Placement (n (%))*	286 (34.4%)	200 (28.0%)	105 (32.0%)
	Work Mode (n (%))*	414 (49.8%)	316 (44.3%)	136 (41.5%)

Note. Values are means (SD) or counts (percentage). One-way ANOVA used for continuous; chi-square for categorical. Significance: *p < 0.05, **p < 0.01, ***p < 0.001.

3. Results

The following sections present the results the sample descriptive results, an overview of AI/ML results from each modeling approach (nested and construct-based), and further explore four exemplar models.

3.1. Sample Descriptive

A total of 1,873 adolescents aged 18 years or younger were included in the analysis, with 1,498 in the training set and 375 in the test set. No significant group differences between the training and test sets were observed in any of the study variables (see Appendix Tables A9-A13 for detailed analysis).

Within the total sample, the mean age was 14.34 years (SD = 2.40), and 51.9% of participants were female. 44.4% of participants residing in Metropolitan Cities, 38.1% in Medium/Small Cities, and 17.5% in Town/Rural Districts. A majority (71.8%) reported that both parents were working, while 7.8% lived in single-parent households and 0.7% identified as being from multicultural families i.e., having at least one foreign-born parent. About 21.8% lived in single-family homes, while the remainder resided in apartments or other multi-unit dwellings. The average monthly household income was 4.25 million KRW (SD = 1.12; approximately 3,100 USD).

3.2. Overview of AI/ML Results

The following sections present the AI/ML results from the nested and construct-based modeling frameworks.

Performance Comparison for Nested AI/ML Classifiers

In the nested framework, 12 nested AI/ML classifiers were trained. Overall, the results show generalizability across training and test sets with consistent mean val loss and test loss of each nested classifier. The baseline model (M0 [Demographics]) performed at chance (AUC = 0.51), and M1 (+Urbanicity) modestly improved performance (AUC = 0.57). Adding a single intent to seek smartphone education item in M2 increased the AUC to 0.63, but further smartphone prevention education-related features in M3 did not yield gains. A substantial improvement emerged in M4 (+Smartphone Use Cases), which added behavioral features related to smartphone use. This model achieved an AUC of 0.81, an 18-point increase, indicating it as a “good test” [58]. We identify the M4 (+Smartphone Use Cases) as our low-risk screener as it offers high performance while using low-burden, non-intrusive features and requires no psychological assessments.

Subsequent models added features related to social context (M5–M7), self-regulation (M8), and perceived digital competence & risk (M9), leading to incremental improvements. The highest performance was observed in M11 (+Consequences & Dependence), which reached an AUC of 0.92 and qualifies as an “excellent test” [58]. However, the inclusion of psychologically sensitive content and longer assessments makes later models less suitable for early-stage or population-level screening for public health surveillance goals. The strength of the M4 (+Smartphone Use Cases) model lies in its balance between predictive power and feasibility (see Table A14 in Appendix D for more details).

Performance Comparison Between Construct-Based AI/ML Classifiers

In our construct-based modeling framework, we train 12 individual, construct-specific AI/ML classifiers. Overall, we find stable performances between the mean val loss and the test loss, indicating generalizability. Three constructs – Smartphone Consequences & Dependence (Smart CD), Perceived Digital Competence & Risk (Perceived DCR), and Smartphone Use Cases (Use Case) – achieve high performances, indicating a “good test” while all others indicate “poor tests” [58]. Notably, we find that the Parental Prevention Efforts and constructs related to smartphone education result in “poor tests” despite qualitatively being related to smartphone overdependence.

3.3. Four Exemplar Models

We present four exemplar models: 1) the M4 (+Smartphone Use Cases) nested model, 2) the Smartphone Consequences & Dependence (Smart CD) construct-based model, 3) the Perceived Digital Competence & Risk (Perceived DCR) construct-based model, and 4) the Smartphone Use Cases (Use Case) construct-based model. For each model, we present the mean val loss, test loss, and AUC (see Table 2 and Figure 1). Next, using XAI techniques, we examine the feature importance across models (see Figure 2 and PDP plots below). We then present the place-stratified results regarding each model’s performance (see Table 3) and relative SHAP feature importance (see Figure 3).

Table 2. Performance metrics across the four exemplar AI/ML models for smartphone overdependence

Model Name/Construct	Shorthand	Algorithm	AUC	Mean Val Loss	Test Loss	Num Features
+Smartphone Use Cases	M4	RF	0.81	0.58	0.55	59
Smartphone Consequences & Dependence	Smart CD	LightGBM	0.89	0.50	0.42	7
Perceived Digital Competence & Risk	Perceived DCR	XGB	0.84	0.52	0.49	34
Smartphone Use Cases	Use Case	XGB	0.80	0.59	0.54	48

Note: We compare AUC (area under the receiver operating characteristic curve), mean validation loss, test loss, and number of features across models. Algorithms used are Random Forest (RF), Light Gradient-Boosting Machine (LightGBM), and Extreme Gradient Boosting (XGBoost).

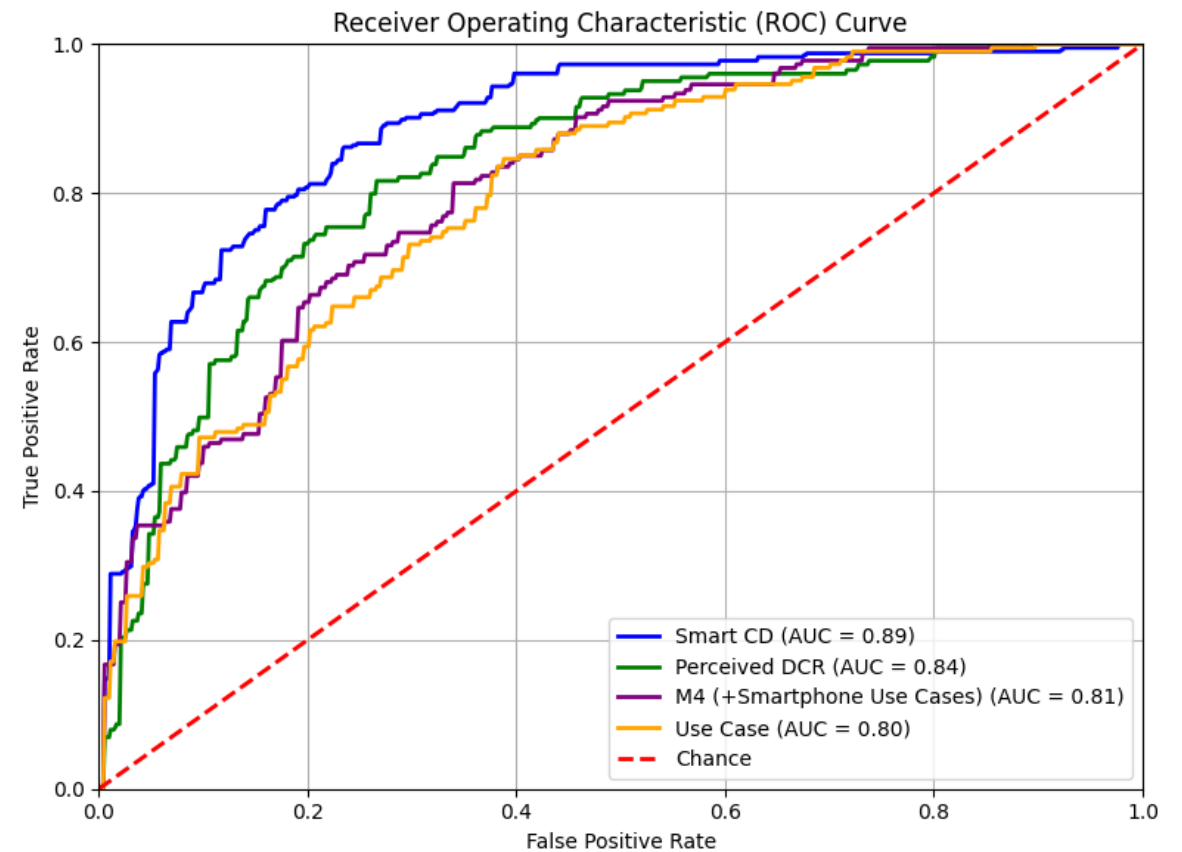


Figure 1. The Area Under the Receiver Operating Characteristic curves (AUC) of the M4 (+Smartphone Use Cases) nested model, the Smartphone Consequences & Dependence (Smart CD) construct-based model, the Perceived Digital Competence & Risk (Perceived DCR) construct-based model, and the Smartphone Use Cases (Use Case) construct-based model are presented.

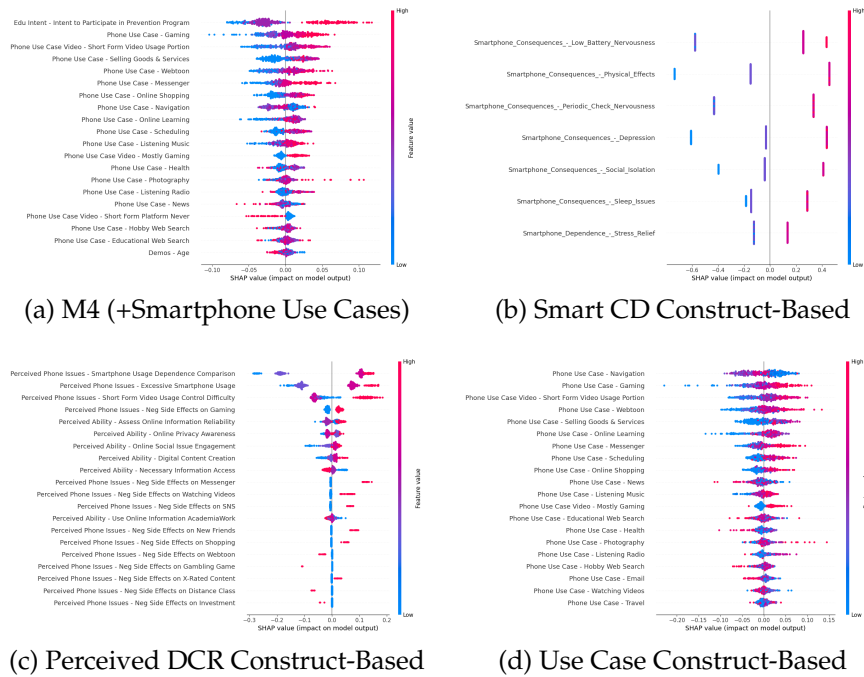


Figure 2. The SHAP beeswarm plots of the M4 (+Smartphone Use Cases) nested model, the Smartphone Consequences & Dependence (Smart CD) construct-based model, the Perceived Digital Competence & Risk (Perceived DCR) construct-based model, and the Smartphone Use Cases (Use Case) construct-based model are presented.

Table 3. AUCs stratified by urbanicity

Model	National AUC	Place-Stratified AUC		
		Metropolitan City	Medium or Small City	Town or Rural District
M4 (+Smartphone Use Cases)	0.81	0.87	0.75	0.80
Smart CD Construct	0.89	0.91	0.87	0.87
Perceived DCR Construct	0.84	0.85	0.83	0.83
Use Case Construct	0.80	0.88	0.70	0.79

Note: The place-stratified AUCs of the M4 (+Smartphone Use Cases) nested model, the Smartphone Consequences & Dependence (Smart CD) construct-based model, the Perceived Digital Competence & Risk (Perceived DCR) construct-based model, and the Smartphone Use Cases (Use Case) construct-based model are presented.

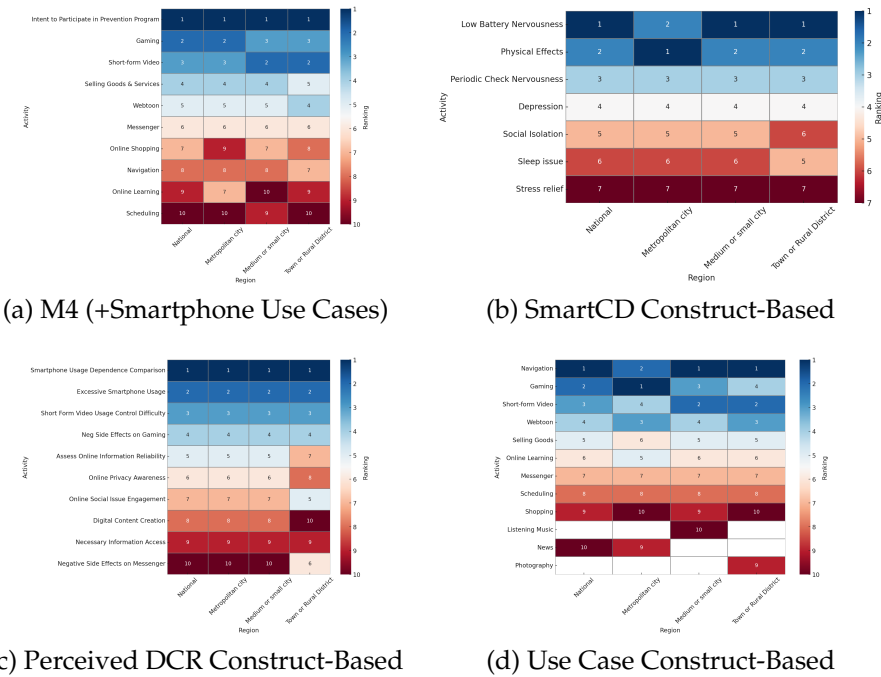


Figure 3. The place-stratified SHAP feature importance rankings of the M4 (+Smartphone Use Cases) nested model, the Smartphone Consequences & Dependence (Smart CD) construct-based model, the Perceived Digital Competence & Risk (Perceived DCR) construct-based model, and the Smartphone Use Cases (Use Case) construct-based model are presented.

3.3.1. M4 (+Smartphone Use Cases) Nested Model

Of the 12 nested classifiers, the M4 (+Smartphone Use Cases) model is the best candidate for a low-risk screener with detection and public health surveillance goals in mind. This model is parsimonious, using 59/131 features, and balances the tradeoff between high-performance (AUC=0.81; Figure 1) and minimizing psychological discomfort. The majority of the predictive power comes from the adolescent’s behavioral use cases of their smartphone requiring no psychological reflection, assessment, or discomfort. These features added a substantial improvement of 18 percentage points, going from an AUC of 0.63 in M3 to 0.81 in M4, achieving a “good test” designation [58]. In addition, this model shows good generalizability across training and test sets with stable mean val loss (0.58) and test loss (0.55) scores.

Feature Importance

The SHAP beeswarm plot for M4 (+Smartphone Use Cases) is presented in Figure 2, subplot (a). Overall, higher endorsement of these features predicted a higher likelihood of being at risk for smartphone overdependency. Some notable nuances are that "Edu Intent" (3-point Likert) was the most important and appears to have a thresholding effect, where only high endorsement (red) led to a higher likelihood of smartphone overdependency. In the PDP, this results in only the endorsement of 3 being associated with a likelihood of overdependency (Figure 4, subplot A.). In contrast, the "Gaming" (8-point Likert) and "Short Form Video Usage Portion" (4-point Likert) features indicate a clear positive relationship where higher endorsement (red) is associated with a higher likelihood of overdependency. The PDPs for both features show a linear trend (Figures 4, subplot B. and subplot C.). The PDPs also revealed a notable nonlinear trend in the marginal effect of "Phone Use Case - Navigation" (7-point Likert), where extreme low (0-1) and high (4-6) levels of endorsement led to a higher likelihood of overdependency while only medium (2-3) levels of endorsement led to a lower likelihood (Figure 4, subplot D.). This may be due to the integral use of smartphones for navigation, where not using it at all is out of the norm and may indicate overuse of other use cases, while overuse would increase reliance and dependency on one’s smartphone (See Appendix E for all other PDPs).

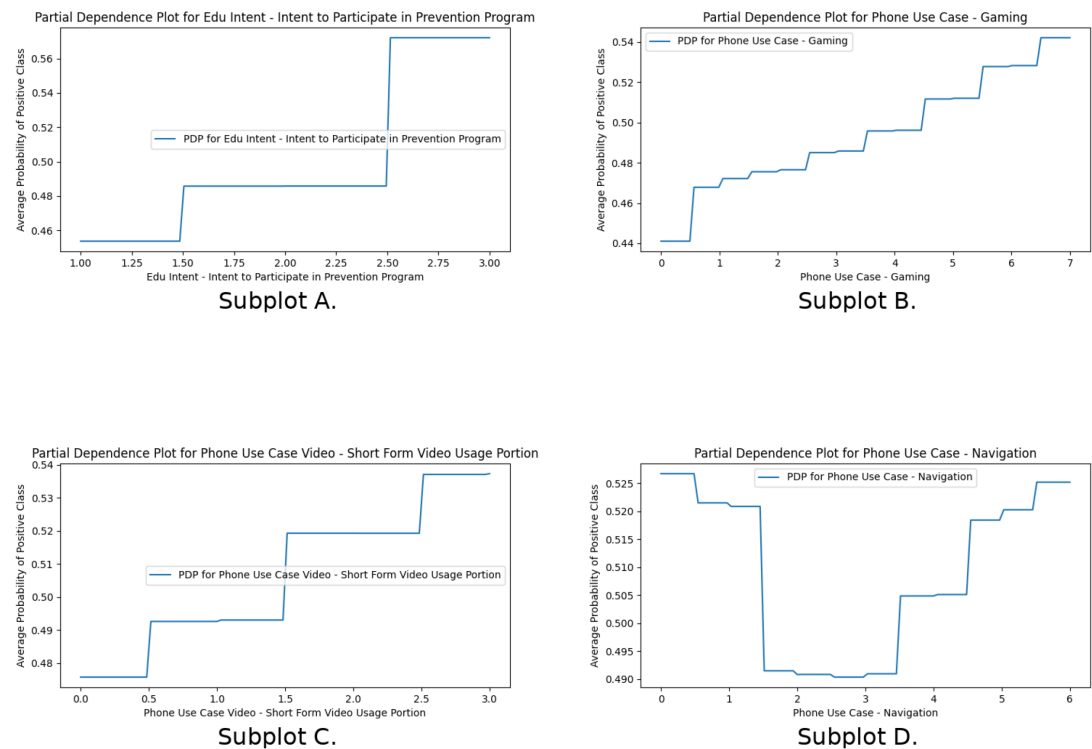


Figure 4. Partial Dependence Plots (PDP) of select features in the Nested M4 (+Smartphone Use Cases) model. Subplot A. shows the PDP for "Edu Intent - Intent to Participate in Prevention Program". Subplot B. "Phone Use Case - Gaming" shows the PDP for Subplot C. "Phone Use Case Video - Short Form Video Usage Portion" shows the PDP for Subplot D. shows the PDP for "Phone Use Case - Navigation".

Place-Stratified Results

Place-stratified analyses revealed that Metropolitan City adolescents have the highest performance, with an AUC of 0.87 (compared to 0.81 in the National performance; Table 3). In contrast, the performance among Medium/Small City adolescents is the lowest, with an AUC of 0.75, which would only indicate a “fair test” [58]. Among Town/Rural District adolescents, the discriminative power remains about the same, with an AUC of 0.80.

Placed-Stratified Feature Importance

Place-stratified analysis of SHAP feature importance found that across all strata, "Edu Intent - Intent to Participate in Prevention Program", "Phone Use Case - Gaming", and "Phone Use Case Video - Short Form" consistently ranked as the top three predictors of smartphone overdependency. "Phone Use Case - Navigation" ranked moderately across all regions, appearing between 7th and 8th in all strata, with no major fluctuations in relative importance. Additionally, “Phone Use Case-Online Learning” ranked higher in Metropolitan Cities (7th) compared to the National and Town/Rural District strata (both 9th), and was the lowest in Medium/Small Cities (10th). In Town/Rural Districts, "Phone Use Case - Webtoon" was ranked 4th—one position higher than in other regions—exceeding "Phone Use Case - Selling Goods and Services”, which ranked 5th. Overall, the place-stratified results show strong consistency in the top-ranked predictors, with minor differences in mid- and lower-ranked features by regional context.

3.3.2. Smartphone Consequences & Dependence Classifier Results

The Smart CD model had the highest performance across all construct-based models with an AUC of 0.89. However, this construct asks adolescents to do the highest degree of intrusive reflection specific to their potential problems and dependency issues related to their smartphone use. Therefore,

it is not surprising that it is the most predictive, but it also carries the largest potential for psychological discomfort.

Feature Importance

The SHAP beeswarm plot for the Smart CD model is presented in Figure 2, subplot (b). We find that consequences are more predictive than the dependence on smartphones for "Stress Relief". PDPs revealed three patterns of marginal effects: 1) linear, step-wise increase, 2) thresholding effect, and 3) binary effect. "Social Isolation" (3-point Likert) followed the linear, step-wise increase. "Physical Effects" (4-point Likert) and "Depression" (4-point Likert) followed the thresholding effect, where there was an initial increase in predicted probability of overdependence that later flattens out. "Stress Relief" (4-point Likert), "Low Battery Nervousness" (4-point Likert), "Sleep Issues" (4-point Likert), and "Periodic Check Nervousness" (4-point Likert) followed the binary effect. Figure 5 shows examples of each pattern (See Appendix F for all other PDPs).

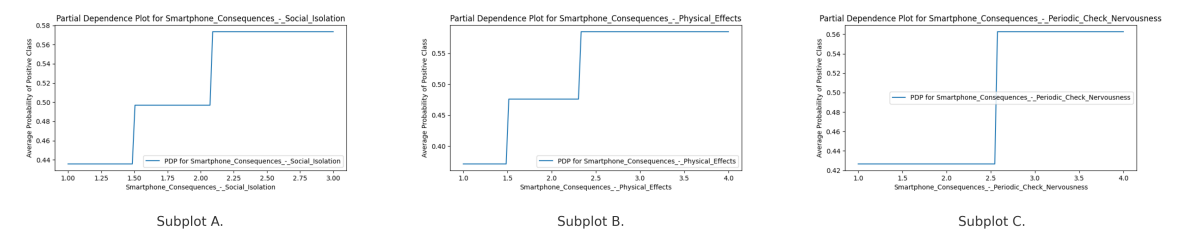


Figure 5. PDP examples of the three marginal effects patterns from the Smart CD model. Subplot A. shows "Social Isolation" as the linear, step-wise increase pattern; Subplot B. shows the "Physical Effects" as the thresholding effect pattern; and Subplot C. shows the "Periodic Check Nervousness" as the binary effect pattern.

Place-Stratified Results

The Smart CD model performance between the National and stratified by urbanicity samples are presented in Table 3. The results show that the performance among Metropolitan City adolescents is the highest with an AUC of 0.91, indicating an “excellent test” [58]. Both the performances among Medium/Small City and Town/Rural District adolescents are the same, with an AUC of 0.87, performing slightly worse than the National model but still in the “good test” range [58].

Placed-Stratified Feature Importance

Place-stratified analysis of SHAP feature importance found that across all strata—National, Metropolitan City, Medium/Small City, and Town/Rural District— "Low Battery Nervousness", "Physical Effects", and "Periodic Check Nervousness" consistently appeared as the top contributors to the predicted probability of smartphone overdependence. In the Metropolitan City stratum, "Physical Effects" was the most important feature, followed by "Low Battery Nervousness" and "Periodic Check Nervousness". This ordering differs from the overall National model, where "Physical Effects" ranked slightly lower. In the Medium/Small City stratum, the top-ranked features mirrored those of the National sample, with "Low Battery Nervousness" and "Physical Effects" leading in importance. In the Town/Rural District stratum, "Low Battery Nervousness" and "Physical Effects" again ranked highest. Notably, “Sleep Issues” appeared slightly more prominently in this group than in the others. Across all regions, all Smart CD features contributed positively to predicted overdependence when endorsed at higher levels. Feature rank order varied only slightly between strata, indicating overall stability in the predictor structure across places.

3.3.3. Perceived Digital Competence & Risk Classifier Results

Next, the Perceived DCR model achieves an AUC of 0.84 and asks questions regarding one’s self-perceptions rather than experienced harms.

Feature Importance

SHAP analysis revealed mixed results where higher endorsement (red) of perceived phone issues was often associated with a higher likelihood of overdependency and higher endorsement of perceived ability was often protective (Figure 2, subplot (c)). Several deviant cases are discussed. "Perceived Phone Issues - Short Form Video Usage Control Difficulty" (4-point Likert) revealed that moderate endorsement was more protective than low endorsement. This may reflect instances of denial in use control difficulties. "Perceived Ability - Assess Online Information Reliability" and "Perceived Ability - Online Privacy Awareness" were not protective, and higher endorsement (red) predicted higher likelihoods for overdependency, perhaps reflecting illusions of control and cognitive distortions. "Perceived Ability - Online Social Issue Engagement" and "Perceived Ability - Digital Content Creation" were also not protective and may reflect a higher reliance on smartphones for socialization and creativity. Three notable parabolic or higher-order trends emerged for the Perceived DCR model PDPs in their marginal effects: 1) a positive to negative curve, 2) a negative to positive curve, and 3) a positive to negative to positive curve, revealing complex cognitive patterns in smartphone overdependency. Figure 6 shows examples of each pattern (See Appendix G for all other PDPs).

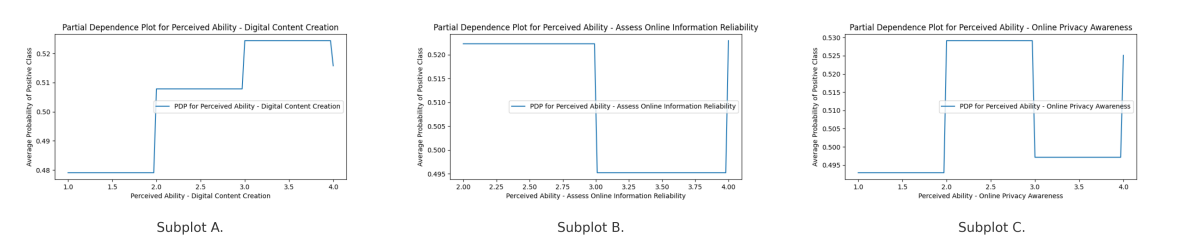


Figure 6. PDP examples of the three marginal effects patterns from the Perceived DCR model. Subplot A. shows "Perceived Ability – Digital Content Creation" as the positive to negative curve; Subplot B. shows the "Perceived Ability – Assess Online Information Reliability" as the negative to positive curve; and Subplot C. shows the "Perceived Ability – Online Privacy Awareness" as the positive to negative to positive curve.

Place-Stratified Results

The performance of the Perceived DCR model stratified by urbanicity is presented in Table 3. Across all strata, the performance remains in the “good test” range. Among Metropolitan City adolescents, the AUC is 0.85, while among both the Medium/Small City and Town/Rural District adolescents, the AUC is 0.83.

Placed-Stratified Feature Importance

Across all strata, three perceived phone issues consistently ranked highest: “Smartphone Overdependence”, “Excessive Smartphone Using Time”, and "Short Form Video Usage Control Difficulty". These self-perceived issues demonstrated stable predictive strength across Metropolitan and Medium/Small cities. In contrast, the Town/Rural District stratum showed slight reordering in feature importance. While “Smartphone Overdependence” and “Excessive Smartphone Using Time” remained top predictors, "Negative side effect on gaming" ranked higher than "Short Form Video Usage Control Difficulty", and "Perceived Ability - Online Social Issue Engagement" appeared more prominently. Specifically, "Online Social Issue Engagement" ranked 5th in the Rural/Town stratum (vs. 7th in others), and "Negative Side Effects on Messenger" ranked 6th (vs. 10th in others). Overall, while the top self-perceived dependence and usage difficulty features remained stable across regions, the Town/Rural District model showed relatively greater importance for social and emotional factors—such as issue engagement and messaging-related effects—while cognitive-evaluative skills and digital production activities showed relatively reduced predictive influence.

3.3.4. Smartphone Use Cases Results

The final “good test” classifier is the Use Case model with an AUC of 0.80, which only uses behavioral tracking related indicators. The Use Case model suggests potential in leveraging raw behavioral tracking data directly from smartphones.

Feature Importance

SHAP analysis revealed nuances in which types of smartphone use cases are predictive of overdependency (Figure 2, subplot (d)). 13 of the top 20 important use cases had a predominantly positive relationship, where higher endorsement (red) was associated with overdependency. The three most important features of this pattern were "Gaming", "Short Form Video Usage Portion", and "Webtoon". Four of the top 20 features had a predominantly negative relationship, where lower endorsement (blue) was associated with overdependency. The three most important features of this pattern were "Navigation", "News", and "Health". This may reflect a bifurcation where smartphone use cases for entertainment are more likely to predict overdependency, while use cases that capture a non-entertainment utility value are more protective. The Use Case PDPs generally supported the SHAP findings with minor nuances or thresholding effects across Likert responses, but still held overall positive or negative trends. Notably, the PDP of the "Navigation" (7-point Likert) feature was consistent with the nested M4 (+Smartphone Use Cases) model, where the same trend and cutoffs were found. Extreme low (0-1) and high (4-6) levels of endorsement led to a higher likelihood of overdependency while only medium (2-3) levels of endorsement led to a lower likelihood. This consistency across models supports the robustness of this feature’s relationship. Figure 7 shows examples and presents the "Navigation" PDPs (See Appendix H for all other PDPs).

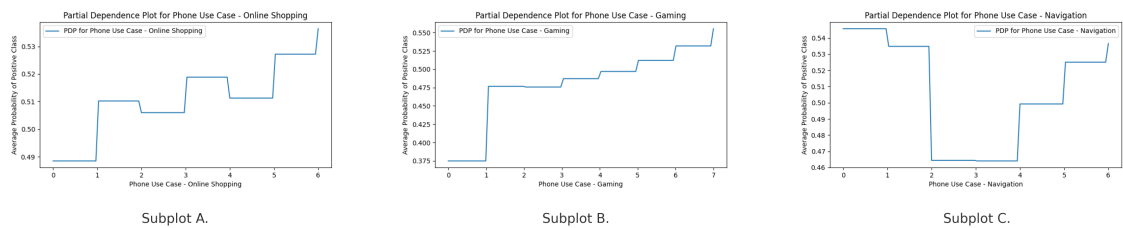


Figure 7. PDP examples and of the "Navigation" feature from the Use Case model. Subplot A. shows "Phone Use Case – Online Shopping" with several dips but overall retaining a positive relationship; Subplot B. shows the "Phone Use Case – Gaming" with an initial thresholding jump but overall retaining a positive relationship; and Subplot C. shows the "Phone Use Case - Navigation" with a parabolic curve.

Place-Stratified Results

The performance of the Use Case model stratified by urbanicity is presented in Table 3. These results show that among Metropolitan City adolescents, there is a substantial jump in performance with an increase of 8 percentage points for an AUC of 0.88. However, the performance substantially drops for the Medium/Small City adolescents with a decrease of 10 percentage points for an AUC of 0.70 falling into the “fair test” range [58]. The performance among Town/Rural Districts decreases marginally to 0.79 but falls from a “good test” to “fair test” [58].

Placed-Stratified Feature Importance

Across all strata, four features consistently emerged as top predictors: "Gaming", "Short-Form Video Usage Portion", "Webtoon", and "Navigation". "Gaming", "Short-Form Video Usage Portion", and "Webtoon" consistently showed strong positive contributions to predicted risk. "Navigation" was the only feature with a mixed effect, consistently ranked in the top but associated with slightly lower predicted risk at moderate levels of use. In the Metropolitan City stratum, "Gaming" ranked first, followed by "Navigation", "Webtoon", and "Short-Form Video Usage Portion". Phone use for "News" showed negative contributions to predictions in this stratum. Overall, behavioral features with immersive or compulsive qualities dominated. In the Medium/Small City stratum, "Navigation"

and "Short-Form Video Usage Portion" were the top predictors, followed by "Gaming" and "Webtoon". Notably, "Listening to Music" ranked 10th only in this region, indicating that more passive forms of phone use may be more salient here. In the Town/Rural District stratum, the top four features mirrored those in the National sample. However, there was greater diversity in the top 10 features, including "Photography" (ranked 9th), which did not appear in other regions. This suggests that expressive and leisure-oriented smartphone behaviors play a more prominent role in rural contexts. Features like "Selling Goods & Services", "Online Learning", "Messenger", "Online Shopping", and "Scheduling" were present across all strata with moderate contributions, while "Listening to Music" appeared in all regions except Metropolitan cities, ranking the lowest in predictive strength but showing regional relevance.

4. Discussion

This study is the first to develop a high-performing, low-risk, AI/ML-based screener for adolescent smartphone overdependence in South Korea using conceptually informed modeling and a place-stratified analysis approach. By combining ethical considerations with conceptually-informed design, we identified a parsimonious screening model that balances predictive power with psychological safety. The M4 (+Smartphone Use Cases) model, leveraging only behavioral use data and demographic characteristics, achieved an AUC of 0.81 nationally, and 0.87 in Metropolitan Cities, comparable to more invasive models using psychological assessments. This confirms our working hypothesis that a minimal set of non-invasive indicators can yield strong predictive power.

These results align with prior literature emphasizing the importance of smartphone use patterns, particularly entertainment-related activities, in predicting overdependence [20,63]. Our XAI analyses provided further insight, showing that use cases like gaming and short-form video were strong predictors of risk, while utilitarian use cases such as navigation exhibited a nonlinear pattern, where both low and high engagement signaled higher risk. This thresholding and parabolic trend in use mirrors earlier findings in digital addiction and behavioral tracking, suggesting that moderate use may reflect healthy regulation, whereas extremes indicate dependency [24].

In parallel, our construct-based models expand on the potential of AI/ML conceptual exploration. Our models confirmed the theoretical relevance of both perception and consequence-based constructs. The Smartphone Consequences & Dependence model achieved the highest performance (AUC = 0.89), but its predictive strength likely reflects conceptual redundancy with the overdependence outcome itself. Many items in this construct directly assess perceived harm and experienced behavioral symptoms that closely mirror the criteria used to define smartphone overdependence, limiting their theoretical distinctiveness despite high classification accuracy.

In contrast, the Perceived Digital Competence & Risk model (AUC = 0.84) provides more meaningful theoretical insight. It aligns closely with cognitive-behavioral frameworks by examining how adolescents evaluate and perceive their own ability and issues with smartphone use. Features related to perceived control, awareness of usage patterns, and beliefs about digital competencies correspond to key mechanisms in models of behavioral addiction and cognitive distortions. The nonlinear and parabolic trends observed in this model's PDPs suggest that adolescents' cognitive self-perceptions are complex, potentially involving both denial and overconfidence—patterns well-documented in cognitive-behavioral theory [64]. Notably, some indicators, such as overconfidence in digital literacy, were associated with increased risk, perhaps reflecting distorted cognitions or rationalizations, which merit further psychological investigation. In the following section, we present place-based policy implication profiles based on our place-stratified analysis.

4.1. Place-Based Policy Implication Profiles

We identify tangible implications that can guide place-based policy responses across regional contexts for the prevention and intervention of smartphone overdependence among adolescents.

Metropolitan Cities

In metropolitan areas, adolescents at risk for smartphone overdependency exhibit significant engagement in immersive digital entertainment activities such as gaming and short-form video consumption. These activities frequently coincide with comparatively higher perceived digital competency and varied smartphone uses. Policy approaches in urban contexts should emphasize enhancing self-assessment of abilities and balancing screen engagement with offline activities rather than implementing broad restrictions. School-based initiatives can effectively incorporate media literacy components focused on self-monitoring techniques and healthy smartphone usage discussions among peers. Additionally, considering the high association between anxiety-driven behaviors and smartphone overdependence, integrating targeted mental health services within school systems to directly address compulsive smartphone use behaviors is recommended.

Medium & Small Cities

Adolescents residing in medium and small cities who are at risk of overdependency exhibit diverse smartphone use patterns, including practical applications such as online shopping, scheduling, and educational platforms. Nevertheless, compulsive use of smartphones, notably for stress relief, remains a relevant factor. Policy and interventions in these contexts should deliver contextually tailored educational programs that recognize and address entertainment-driven risks and the normalization of smartphone-based emotional coping strategies. Offering adolescents practical alternatives to smartphone-based coping by enhancing emotional literacy, digital citizenship education, and providing habit-tracking resources could effectively mitigate the risks associated with overdependence.

Towns & Rural Districts

In towns and rural areas, at-risk adolescents predominantly use smartphones for expressive and leisure-related activities such as video streaming and engagement in online social interactions. These patterns may be related to limited offline social opportunities in rural settings. Policy measures for rural adolescents should thus extend beyond limitations on screen time to address underlying structural needs. These measures could include expanding access to offline youth facilities, promoting community-driven activities, and fostering healthy online interaction guidelines. Additionally, considering the moderate predictive value of smartphone use for stress coping, interventions should seek input from adolescents regarding their daily smartphone usage patterns, thereby informing the creation of meaningful and accessible offline alternatives.

4.2. Limitations & Future Research

This study has several limitations. First, all data were derived from self-report surveys, including behavioral indicators. Future research should explore the integration of passive smartphone tracking data, which may offer higher ecological validity and remove social desirability bias. In addition, Ecological Momentary Assessment methods can improve these studies. Second, while we stratified models by urbanicity, other contextual variables—such as school type or family environment—could further refine prediction. Third, while our models were interpretable using SHAP and PDP, further work using longitudinal data is needed to establish causal pathways.

Future studies should also investigate protective features and resilience factors, particularly in adolescents who report high usage but do not develop dependency. Additionally, given the complex, nonlinear relationships found in perceived digital competence & risk indicators, qualitative or mixed-methods research may help unpack underlying cognitive distortions of smartphone use.

5. Conclusions

This study's contributions are both methodological and practical. Methodologically, this study demonstrates the utility of conceptually informed construct modeling over “kitchen sink” approaches. Psychologically salient constructs—particularly those relating to use patterns, perceived digital compe-

tence & risk, and consequences—outperform broader demographic or contextual predictors. Practically, our work supports the adoption of low-burden, adolescent-friendly screeners in school settings, aligning with ethical frameworks (e.g., the Belmont Report; APA Code of Ethics) that call for minimal harm in youth research. Conceptually, this study illustrates the use of AI/ML to uncover potential theoretical phenomena. In our case, cognitive patterns point to potential cognitive distortions. Policy-wise, our work contributes to the growing field of place-based AI/ML by demonstrating that predictive accuracy and feature importance vary significantly by urbanicity. Our results suggest that risk for overdependence is not uniform across regions. Local social, technological, and cultural contexts shape which factors matter most. These findings support the development of regionally tailored public health messaging and digital wellness interventions. Adolescents from medium or small cities consistently showed lower model performance across classifiers, suggesting that these communities may exhibit more heterogeneous or undercaptured patterns of smartphone use. This nuance emphasizes the need for locally adaptive tools and supports critiques that national models risk obscuring regional variation [65].

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Institutional Review Board Statement: This study involved a secondary analysis of publicly available data. The Institutional Review Board at the University of Alabama (ID: 25-02-8385, February 17, 2025) reviewed the protocol and determined that ethical approval was not required, as this manuscript does not involve human subjects research as defined by DHHS and FDA regulations.

Data Availability Statement: The data used in this study were obtained from the Public Data Portal of the Republic of Korea (<https://www.data.go.kr/data/15038425/fileData.do>). This is a publicly available dataset provided by a government agency and does not require special access permission.

Conflicts of Interest: “The authors declare no conflicts of interest.”

Appendix

Appendix A. Conceptual Feature Selection & Construct Grouping

Tables A1 and A2 outline the 2 domains, 10 constructs and 132 features.

Appendix B. Hyperparameters for our 4 Exemplar Models

In Table A3, we present the hyperparameters for our four best-performing models.

Appendix C. Sample Descriptives

The following sections present tables outlining place-stratified and training vs test set descriptive comparisons across all study variables.

Appendix C.1. Place-Stratified Descriptive Comparisons

Tables A4-A6 present the place-stratified descriptive comparisons. One-way ANOVAs are used for continuous and ordinal variables while Chi-square tests are used for categorical ones.

Appendix C.2. Training vs Test Set Descriptive Comparisons

Tables [A9-A13](#) present the training vs test set descriptive comparisons. One-way ANOVAs are used for continuous and ordinal variables while Chi-square tests are used for categorical ones.

Appendix D. AI/ML Results

Appendix D.1. Performance Comparison for Nested AI/ML Classifiers

We present the model performance of the 12 nested AI/ML classifiers in Table [A14](#), which presents the AUCs for several high-performing models.

Appendix D.2. Performance Comparison Between Construct-Based AI/ML Classifiers

We present the model performances of the 12 construct-based AI/ML classifiers in Table [A15](#).

Appendix E. M4 (+Smartphone Use Cases) PDPs

Additional M4 (+Smartphone Use Cases) PDPs are presented in Figures [A1](#), [A2](#), [A3](#), [A4](#), [A5](#), and [A6](#).

Appendix F. Smart CD PDPs

Additional Smart CD PDPs are presented in Figures [A7](#), [A8](#), [A9](#).

Appendix G. Perceived DCR PDPs

Additional Perceived DCR PDPs are presented in Figures [A10](#), [A11](#), [A12](#), [A13](#), [A14](#), [A15](#).

Appendix H. Use Case Only PDPs

Additional Use Case Only PDPs are presented in Figures [A16](#), [A17](#), [A18](#), [A19](#), [A20](#), [A21](#), [A22](#).

Table A1. Conceptual Feature Selection & Construct Grouping (Part 1).

Domains/Constructs	Features
Demographics	Male Age Elementary School Middle School High School
Urbanicity	Metropolitan City Medium/Small City Town/Rural District
Preventive Education Experiences	Smartphone Overdependence Prevention Education Awareness of Smartphone Overdependence Treatment
Intent to Seek Smartphone Education	Intent to Participate in Prevention Program
Smartphone Use Cases	Phone Use Case - Email Phone Use Case - Messenger Phone Use Case - Making New Friends Phone Use Case - Scheduling Phone Use Case - Health Phone Use Case - Zoom Meetings Phone Use Case - Online Shopping Phone Use Case - Selling Goods & Services Phone Use Case - Banking Phone Use Case - Investment Phone Use Case - Gaming Phone Use Case - Watching Videos Phone Use Case - Listening Music Phone Use Case - Listening Radio Phone Use Case - Webtoon Phone Use Case - Photography Phone Use Case - Travel Phone Use Case - Adult Content Phone Use Case - Gambling Phone Use Case - News Phone Use Case - Educational Web Search Phone Use Case - Hobby Web Search Phone Use Case - Navigation Phone Use Case - Online Learning Smartphone Online Video Usage Phone Use Case Video - Short Form Platform YouTube Phone Use Case Video - Short Form Platform TikTok Phone Use Case Video - Short Form Platform Reels Phone Use Case Video - Short Form Platform Etc Phone Use Case Video - Short Form Platform Never Phone Use Case Video - Short Form Video Usage Portion Phone Use Case Video - Mostly Food Phone Use Case Video - Mostly Sports Phone Use Case Video - Mostly Fashion/Beauty Phone Use Case Video - Mostly Gaming Phone Use Case Video - Mostly Dramas/Variety Show Phone Use Case Video - Mostly Animation/Comics Phone Use Case Video - Mostly TV/Entertainment Phone Use Case Video - Mostly Music/Dance Phone Use Case Video - Mostly Talk/Streaming Phone Use Case Video - Mostly Movies Phone Use Case Video - Mostly Products Phone Use Case Video - Mostly Current Affairs Phone Use Case Video - Mostly Lifestyle Phone Use Case Video - Mostly Edu Phone Use Case Video - Mostly Kids Phone Use Case Video - Mostly Vlog Phone Use Case Video - Mostly Other
Home Environment	House Apartment Mansion etc Multicultural Family Single Parent Family Both Parents Work Monthly Family Income
Parental Prevention Efforts	Complete Smartphone Use Restriction Limit Smartphone Usage Time Restrict Smartphone Apps Teach Smartphone Usage Smartphone Use Pros and Cons Recommended Beneficial Smartphone Apps Use Beneficial Apps Together Use Beneficial Games Together Family Smartphone Rules
Social Support	Family Support Generosity Friend Support In Difficulty Society Fair Opportunities and Benefits

Note: Part 2 of this table is presented in Table A2.

Table A2. Conceptual Feature Selection & Construct Grouping (Part 2).

Domains/Constructs	Features
Self-Regulation Assessments	Smartphone Usage Avoid While Walking Smartphone Usage Habits Check Smartphone Usage History Check Digital Detox Designated Smartphone Placement Use Work Mode Direct Conversation Hobby Engagement
Perceived Digital Competence & Risk	Perceived Phone Issues - Smartphone Usage Dependence Comparison Perceived Phone Issues - Neg Side Effects on SNS Perceived Phone Issues - Neg Side Effects on Email Perceived Phone Issues - Neg Side Effects on Messenger Perceived Phone Issues - Neg Side Effects on New Friends Perceived Phone Issues - Neg Side Effects on Scheduling Perceived Phone Issues - Neg Side Effects on Health Perceived Phone Issues - Neg Side Effects on Zoom Perceived Phone Issues - Neg Side Effects on Shopping Perceived Phone Issues - Neg Side Effects on Selling Perceived Phone Issues - Neg Side Effects on Banking Perceived Phone Issues - Neg Side Effects on Investment Perceived Phone Issues - Neg Side Effects on Gaming Perceived Phone Issues - Neg Side Effects on Watching Videos Perceived Phone Issues - Neg Side Effects on Listening Music Perceived Phone Issues - Neg Side Effects on Listening Radio Perceived Phone Issues - Neg Side Effects on Webtoon Perceived Phone Issues - Neg Side Effects on Photography Perceived Phone Issues - Neg Side Effects on Travel Perceived Phone Issues - Neg Side Effects on X-Rated Content Perceived Phone Issues - Neg Side Effects on Gambling Game Perceived Phone Issues - Neg Side Effects on News Perceived Phone Issues - Neg Side Effects on Edu Perceived Phone Issues - Neg Side Effects on Interests Perceived Phone Issues - Neg Side Effects on Navigation Perceived Phone Issues - Neg Side Effects on Distance Class Perceived Phone Issues - Excessive Smartphone Usage Perceived Phone Issues - Short Form Video Usage Control Difficulty Perceived Competence - Necessary Information Access Perceived Competence - Assess Online Information Reliability Perceived Competence - Online Social Issue Engagement Perceived Competence - Digital Content Creation Perceived Competence - Online Privacy Awareness Perceived Competence - Use Online Information Academia Work
Life Satisfaction	Relationship Satisfaction Work Satisfaction Leisure Activities Satisfaction Overall Life Satisfaction
Smartphone Consequences & Dependence	Smartphone Periodic Check Nervousness Smartphone Low Battery Nervousness Smartphone Usage Depression Smartphone Usage Physical Effects Smartphone Usage Sleep Issues Smartphone Communication Social Isolation Stress Relief Through Smartphone

Note: Part 1 of this table is presented in Table A1. Neg. stands for Negative.

Table A3. Hyperparameters for our 4 Best Models

Model Name	Algorithm	Hyperparameters
Nest M4 model	Random Forest	n_estimators = 1967; max_depth = 81; min_samples_split = 4; min_samples_leaf = 1
SmartCD Only	LightGBM	n_estimators = 254; learning_rate = 0.064495018055983; max_depth = 3; num_leaves = 222; min_child_samples = 17; feature_fraction = 0.469378476101846; bagging_fraction = 0.52804982292064; bagging_freq = 6; lambda_l1 = 0.186535833027839; lambda_l2 = 0.0000131738014410991
Perceived DCR Only	XGBoost	num_boost_round = 674; subsample = 0.85597440455654; min_child_weight = 1; max_depth = 38; learning_rate = 0.0127554708475019; γ = 0.229654735805916; colsample_bytree = 0.287803548558039; reg_alpha = 0.00651358918568053; reg_lambda = 0.791652034688638
Use Case Only	XGBoost	num_boost_round = 562; subsample = 0.583206150016204; min_child_weight = 1; max_depth = 74; learning_rate = 0.0113916452910645; γ = 0.00109214155684023; colsample_bytree = 0.300084001241431; reg_alpha = 0.277286668793397; reg_lambda = 0.0305140602390746

Table A4. All 128 One-Hot Encoded Features of Adolescents by Urbanicity: Adolescents Aged 18 Years or Younger (N = 1,873)

Variable Category	Variable	Metropolitan City (n=831)	Medium/Small City (n=714)	Town/Rural District (n=328)	p-value
Demographics	Age (mean, SD)	14.35 (2.35)	14.35 (2.45)	14.29 (2.4)	0.917
	Sex (Male; n (%))	401 (48.3%)	355 (49.7%)	144 (43.9%)	0.215
	Elementary School Students (n (%))	205 (24.7%)	189 (26.5%)	88 (26.8%)	0.637
	Middle School Students (n (%))	317 (38.1%)	263 (36.8%)	127 (38.7%)	0.802
	High School Students (n (%))	309 (37.2%)	262 (36.7%)	113 (34.5%)	0.679
Home Environment	House (n (%))	167 (20.1%)	152 (21.3%)	90 (27.4%)	0.022*
	Apartment (n (%))	473 (56.9%)	394 (55.2%)	172 (52.4%)	0.377
	Mansion (n (%))	170 (20.5%)	129 (18.1%)	53 (16.2%)	0.197
	Other Housing (n (%))	21 (2.5%)	39 (5.5%)	13 (4.0%)	-
	Multicultural Family (n (%))	7 (0.8%)	2 (0.3%)	4 (1.2%)	-
	Single-Parent Family (n (%))	55 (6.6%)	60 (8.4%)	31 (9.5%)	0.200
	Both Parents Working (n (%))	588 (70.8%)	520 (72.8%)	236 (72.0%)	0.664
	Monthly Household Income (mean, SD)	3.26 (0.75)	3.2 (0.82)	3.23 (0.77)	0.424
Smartphone Use Cases	Email (M (SD))	1.85 (1.89)	1.89 (1.89)	1.98 (2.05)	0.601
	Messenger (M (SD))	5.31 (1.46)	5.41 (1.42)	5.02 (1.75)	<0.001***
	Making New Friends (M (SD))	1.45 (1.98)	1.25 (1.79)	1.33 (1.85)	0.126
	Scheduling (M (SD))	2.06 (2.13)	1.86 (2.06)	1.62 (2.08)	0.004**
	Health (M (SD))	1.76 (2.04)	1.59 (1.91)	1.46 (1.98)	0.045*
	Zoom Meetings (M (SD))	0.73 (1.57)	0.54 (1.33)	0.59 (1.41)	0.030*
	Online Shopping (M (SD))	2.1 (2.16)	2.04 (2.13)	2.18 (2.32)	0.596
	Selling Goods & Services (M (SD))	1.65 (2.06)	1.51 (2.0)	1.77 (2.27)	0.149
	Banking (M (SD))	1.49 (1.93)	1.39 (1.85)	1.35 (2.01)	0.411
	Investment (M (SD))	0.86 (1.52)	0.63 (1.28)	0.62 (1.29)	<0.001***
	Gaming (M (SD))	4.89 (1.83)	4.92 (1.73)	4.63 (1.97)	0.052
	Watching Videos (M (SD))	5.25 (1.62)	5.32 (1.58)	5.02 (1.81)	0.018*
	Listening Music (M (SD))	4.51 (1.97)	4.48 (2.04)	4.03 (2.35)	<0.001***
	Listening Radio (M (SD))	1.55 (2.03)	1.69 (2.08)	1.54 (2.09)	0.380
	Webtoon (M (SD))	3.35 (2.27)	3.32 (2.2)	3.11 (2.33)	0.241

Table A5. All 128 One-Hot Encoded Features of Adolescents by Urbanicity (continued): Smartphone Use Cases

Variable Category	Variable	Metropolitan City (n=831)	Medium/Small City (n=714)	Town/Rural District (n=328)	p-value
	Photography (M (SD))	3.5 (1.96)	3.43 (1.94)	3.42 (2.2)	0.745
	Travel (M (SD))	1.71 (1.94)	1.6 (1.86)	1.84 (2.04)	0.144
	Adult Content (M (SD))	0.5 (1.15)	0.33 (0.94)	0.3 (0.94)	<0.001***
	Gambling (M (SD))	0.48 (1.2)	0.29 (0.87)	0.32 (1.04)	<0.001***
	News (M (SD))	2.57 (2.21)	2.3 (2.04)	2.16 (2.16)	0.004**
	Educational Web Search (M (SD))	4.06 (1.81)	3.84 (1.78)	3.64 (2.26)	0.002**
	Hobby Web Search (M (SD))	3.87 (1.9)	3.73 (1.9)	3.68 (2.25)	0.234
	Navigation (M (SD))	2.42 (1.92)	2.37 (1.95)	2.12 (2.0)	0.049*
	Online Learning (M (SD))	3.63 (2.23)	3.45 (2.2)	3.62 (2.33)	0.274
	Smartphone Online Video Usage (n (%))	798 (96.0%)	694 (97.2%)	313 (95.4%)	0.285
	Short Form Platform YouTube (n (%))	443 (53.3%)	315 (44.1%)	162 (49.4%)	0.002**
	Short Form Platform TikTok (n (%))	145 (17.4%)	165 (23.1%)	68 (20.7%)	0.021*
	Short Form Platform Reels (n (%))	77 (9.3%)	81 (11.3%)	34 (10.4%)	0.405
	Short Form Platform Etc (n (%))	8 (1.0%)	6 (0.8%)	2 (0.6%)	-
	Short Form Platform Never (n (%))	125 (15.0%)	127 (17.8%)	47 (14.3%)	0.229
	Short Form Video Usage (M (SD))	1.67 (1.1)	1.73 (1.15)	1.8 (1.17)	0.207
	Mostly Food (n (%))	130 (15.6%)	80 (11.2%)	47 (14.3%)	0.038*
	Mostly Sports (n (%))	40 (4.8%)	39 (5.5%)	14 (4.3%)	-
	Mostly Fashion/Beauty (n (%))	38 (4.6%)	37 (5.2%)	20 (6.1%)	-
	Mostly Gaming (n (%))	250 (30.1%)	222 (31.1%)	90 (27.4%)	0.489
	Mostly Dramas/Variety Show (n (%))	83 (10.0%)	54 (7.6%)	24 (7.3%)	-
	Mostly Animation/Comics (n (%))	56 (6.7%)	63 (8.8%)	24 (7.3%)	-
	Mostly TV/Entertainment (n (%))	42 (5.1%)	46 (6.4%)	19 (5.8%)	-
	Mostly Music/Dance (n (%))	45 (5.4%)	53 (7.4%)	24 (7.3%)	-
	Mostly Talk/Streaming (n (%))	17 (2.0%)	16 (2.2%)	5 (1.5%)	-
	Mostly Movies (n (%))	18 (2.2%)	9 (1.3%)	8 (2.4%)	-
	Mostly Products (n (%))	12 (1.4%)	11 (1.5%)	2 (0.6%)	-
	Mostly Current Affairs (n (%))	3 (0.4%)	10 (1.4%)	2 (0.6%)	-
	Mostly Lifestyle (n (%))	4 (0.5%)	2 (0.3%)	5 (1.5%)	-
	Mostly Edu (n (%))	49 (5.9%)	34 (4.8%)	26 (7.9%)	-
	Mostly Kids (n (%))	6 (0.7%)	11 (1.5%)	2 (0.6%)	-
	Mostly Vlog (n (%))	4 (0.5%)	7 (1.0%)	1 (0.3%)	-
	Mostly Other (n (%))	1 (0.1%)	0 (0.0%)	0 (0.0%)	-

Table A6. All 128 One-Hot Encoded Features of Adolescents by Urbanicity (continued): Psychosocial Factors, Consequences, Regulation, Support, Satisfaction

Variable Category	Variable	Metropolitan City (n=831)	Medium/Small City (n=714)	Town/Rural District (n=328)	p-value
Perceived Digital Risk					
	Smartphone Usage Dependence Comparison (M (SD))	2.71 (0.74)	2.76 (0.75)	2.72 (0.78)	0.376
	Side Effects on SNS (n (%))	48 (5.8%)	56 (7.8%)	22 (6.7%)	-
	Side Effects on Email (n (%))	15 (1.8%)	11 (1.5%)	4 (1.2%)	-
	Side Effects on Messenger (n (%))	23 (2.8%)	28 (3.9%)	16 (4.9%)	-
	Side Effects on New Friends (n (%))	21 (2.5%)	16 (2.2%)	14 (4.3%)	-
	Side Effects on Scheduling (n (%))	13 (1.6%)	4 (0.6%)	0 (0.0%)	-
	Side Effects on Health (n (%))	7 (0.8%)	2 (0.3%)	1 (0.3%)	-
	Side Effects on Zoom (n (%))	3 (0.4%)	5 (0.7%)	0 (0.0%)	-
	Side Effects on Shopping (n (%))	34 (4.1%)	24 (3.4%)	13 (4.0%)	-
	Side Effects on Selling (n (%))	8 (1.0%)	7 (1.0%)	6 (1.8%)	-
	Side Effects on Banking (n (%))	1 (0.1%)	3 (0.4%)	2 (0.6%)	-
	Side Effects on Investment (n (%))	9 (1.1%)	3 (0.4%)	3 (0.9%)	-
	Side Effects on Gaming (n (%))	353 (42.5%)	313 (43.8%)	108 (32.9%)	0.003**
	Side Effects on Watching Videos (n (%))	68 (8.2%)	52 (7.3%)	21 (6.4%)	-
	Side Effects on Listening Music (n (%))	0 (0.0%)	2 (0.3%)	3 (0.9%)	-
	Side Effects on Listening Radio (n (%))	1 (0.1%)	1 (0.1%)	1 (0.3%)	-
	Side Effects on Webtoon (n (%))	28 (3.4%)	13 (1.8%)	7 (2.1%)	-
	Side Effects on Photography (n (%))	2 (0.2%)	0 (0.0%)	1 (0.3%)	-
	Side Effects on Travel (n (%))	1 (0.1%)	1 (0.1%)	0 (0.0%)	-
	Side Effects on X-Rated Content (n (%))	30 (3.6%)	9 (1.3%)	8 (2.4%)	-
	Side Effects on Gambling Game (n (%))	2 (0.2%)	12 (1.7%)	2 (0.6%)	-
	Side Effects on News (n (%))	3 (0.4%)	1 (0.1%)	2 (0.6%)	-
	Side Effects on Edu (n (%))	1 (0.1%)	3 (0.4%)	0 (0.0%)	-
	Side Effects on Interests (n (%))	1 (0.1%)	0 (0.0%)	0 (0.0%)	-
	Side Effects on Navigation (n (%))	2 (0.2%)	3 (0.4%)	0 (0.0%)	-
	Side Effects on Distance Class (n (%))	1 (0.1%)	5 (0.7%)	4 (1.2%)	-
	Excessive Smartphone Usage (M (SD))	2.57 (0.69)	2.62 (0.69)	2.62 (0.77)	0.218
	Short Form Video Usage Control Difficulty (M (SD))	1.71 (1.09)	1.81 (1.15)	1.81 (1.08)	0.139
Perceived Digital Competence					
	Necessary Information Access (M (SD))	3.25 (0.64)	3.25 (0.66)	3.3 (0.67)	0.404
	Assess Online Information Reliability (M (SD))	2.98 (0.75)	2.94 (0.77)	3.05 (0.78)	0.070
	Online Social Issue Engagement (M (SD))	2.8 (0.85)	2.7 (0.85)	2.81 (0.81)	0.037*
	Digital Content Creation (M (SD))	2.49 (0.98)	2.43 (0.98)	2.62 (0.99)	0.012*
	Online Privacy Awareness (M (SD))	2.66 (0.88)	2.57 (0.86)	2.79 (0.86)	<0.001***
	Use Online Information for Academia/Work (M (SD))	2.89 (0.87)	2.67 (0.94)	2.81 (0.92)	<0.001***

Table A7. All 128 One-Hot Encoded Features of Adolescents by Urbanicity (continued): Psychosocial Factors, Consequences, Regulation, Support, Satisfaction

Variable Category	Variable	Metropolitan City (n=831)	Medium/Small City (n=714)	Town/Rural District (n=328)	p-value
Smartphone Consequences & Dependence					
	Low Battery Nervousness (M (SD))	2.71 (0.83)	2.85 (0.86)	2.75 (0.85)	0.004**
	Smartphone Usage Depression (M (SD))	2.16 (0.87)	2.23 (0.81)	2.17 (0.83)	0.250
	Physical Effects (M (SD))	2.27 (0.89)	2.35 (0.86)	2.32 (0.89)	0.170
	Periodic Check Nervousness (M (SD))	2.57 (0.75)	2.61 (0.76)	2.52 (0.73)	0.175
	Smartphone Usage Sleep Issues (M (SD))	2.21 (0.84)	2.29 (0.86)	2.21 (0.89)	0.174
	Social Isolation (M (SD))	2.05 (0.79)	2.13 (0.81)	2.11 (0.73)	0.133
	Stress Relief Through Smartphone (M (SD))	2.41 (0.83)	2.43 (0.85)	2.35 (0.85)	0.437
Preventative Education					
	Received Preventive Education (n (%))	589 (31.4%)	466 (31.1%)	123 (32.8%)	0.819
	Awareness of Treatment Options (n (%))	958 (51.1%)	768 (51.3%)	190 (50.7%)	0.979
Intent to Seek Smartphone Education					
	Participation Intention (M (SD))	2.25 (0.71)	2.21 (0.72)	2.27 (0.74)	0.370
Parental Prevention Efforts					
	Complete Restriction (n (%))	81 (9.7%)	71 (9.9%)	33 (10.1%)	0.984
	Teaches How to Use the Phone Use (n (%))	397 (47.8%)	284 (39.8%)	130 (39.6%)	0.002**
	Restrict Smartphone Apps (n (%))	508 (61.1%)	439 (61.5%)	185 (56.4%)	0.256
	Teaches Pros and Cons (n (%))	514 (61.9%)	422 (59.1%)	176 (53.7%)	0.037*
	Recommends Good Apps (n (%))	396 (47.7%)	277 (38.8%)	152 (46.3%)	<0.001***
	Uses Good Apps Together (n (%))	252 (30.3%)	210 (29.4%)	93 (28.4%)	0.793
	Plays Good Games Together (n (%))	225 (27.1%)	206 (28.9%)	75 (22.9%)	0.130
	Family Smartphone Rules (n (%))	354 (42.6%)	272 (38.1%)	133 (40.5%)	0.199
Social Support					
	Family Support (M (SD))	3.29 (0.69)	3.17 (0.75)	3.26 (0.66)	0.005**
	Friend Support (M (SD))	3.13 (0.67)	3.07 (0.69)	3.17 (0.68)	0.044*
	Societal Fairness Perception (M (SD))	2.93 (0.71)	2.81 (0.75)	3.03 (0.79)	<0.001***

Table A8. All 128 One-Hot Encoded Features of Adolescents by Urbanicity (continued): Psychosocial Factors, Consequences, Regulation, Support, Satisfaction

Variable Category	Variable	Metropolitan City (n=831)	Medium/Small City (n=714)	Town/Rural District (n=328)	p-value
Social Support	Family Support (M (SD))	3.29 (0.69)	3.17 (0.75)	3.26 (0.66)	0.005**
	Friend Support (M (SD))	3.13 (0.67)	3.07 (0.69)	3.17 (0.68)	0.044*
	Societal Fairness Perception (M (SD))	2.93 (0.71)	2.81 (0.75)	3.03 (0.79)	<0.001***
Self-Regulation Assessments					
	Smartphone Usage Avoid While Walking (n (%))	518 (62.3%)	455 (63.7%)	223 (68.0%)	0.195
	Smartphone Usage Habits Check (n (%))	226 (27.2%)	186 (26.1%)	96 (29.3%)	0.554
	Smartphone Use History Check (n (%))	164 (19.7%)	162 (22.7%)	72 (22.0%)	0.347
	Digital Detox (n (%))	210 (25.3%)	153 (21.4%)	55 (16.8%)	0.006**
	Designated Placement (n (%))	286 (34.4%)	200 (28.0%)	105 (32.0%)	0.026*
	Use of Work Mode (n (%))	414 (49.8%)	316 (44.3%)	136 (41.5%)	0.015*
	Engaging in Conversation (n (%))	374 (45.0%)	285 (39.9%)	134 (40.9%)	0.109
	Hobby Engagement (n (%))	208 (25.0%)	212 (29.7%)	94 (28.7%)	0.106
Life Satisfaction					
	Relationship Satisfaction (M (SD))	3.25 (0.58)	3.28 (0.6)	3.31 (0.6)	0.193
	Work Satisfaction (M (SD))	2.91 (0.7)	2.89 (0.73)	2.99 (0.72)	0.077
	Leisure Satisfaction (M (SD))	2.86 (0.7)	2.84 (0.71)	2.91 (0.77)	0.300
	Overall Life Satisfaction (M (SD))	3.08 (0.57)	3.04 (0.59)	3.08 (0.65)	0.462

Note. p-values are based on comparisons between the different urbanicity strata when cell sizes > 29. One-way ANOVA was used for continuous variables; Pearson’s chi-square test was used for categorical variables. *p < .05, **p < .01, ***p < .001 considered statistically significant.

Table A9. All 131 One-Hot Encoded Features of Descriptive Characteristics of the Sample by Training and Test Sets (Aged 18 or Younger, $N = 1,873$)

Variable Category	Variable	Total Sample (N=1,873)	Training Set (n=1,498)	Test Set (n=375)	p-value
Demographics	Age (mean, SD)	14.34 (2.40)	14.34 (2.39)	14.34 (2.42)	1.000
	Sex (Male; n (%))	900 (48.1%)	728 (48.6%)	172 (45.9%)	0.639
	Elementary School Students (n (%))	482 (25.7%)	389 (26.0%)	93 (24.8%)	0.898
	Middle School Students (n (%))	707 (37.7%)	565 (37.7%)	142 (37.9%)	0.999
	High School Students (n (%))	684 (36.5%)	544 (36.3%)	140 (37.3%)	0.935
Urbanicity	Metropolitan City (n (%))	831 (44.4%)	656 (43.8%)	175 (46.7%)	0.605
	Medium or Small City (n (%))	714 (38.1%)	571 (38.1%)	143 (38.1%)	1.000
	Town or Rural District (n (%))	328 (17.5%)	271 (18.1%)	57 (15.2%)	0.420
Home Environment	House (n (%))	409 (21.8%)	331 (22.1%)	78 (20.8%)	0.863
	Apartment (n (%))	1,039 (55.5%)	829 (55.3%)	210 (56.0%)	0.974
	Mansion (n (%))	352 (18.8%)	276 (18.4%)	76 (20.3%)	0.716
	Other Housing (n (%))	73 (3.9%)	62 (4.1%)	11 (2.9%)	-
	Multicultural Family (n (%))	13 (0.7%)	11 (0.7%)	2 (0.5%)	-
	Single-Parent Family (n (%))	146 (7.8%)	114 (7.6%)	32 (8.5%)	0.837
	Both Parents Working (n (%))	1,344 (71.8%)	1,086 (72.5%)	258 (68.8%)	0.364
	Monthly Household Income (mean, SD)	3.23 (0.78)	3.24 (0.79)	3.18 (0.76)	0.442

Table A10. All 131 One-Hot Encoded Features (continued): Smartphone Use Cases

Variable Category	Variable	Total Sample (N=1,873)	Training Set (n=1,498)	Test Set (n=375)	p-value
Smartphone Use Cases					
	Email (M (SD))	1.89 (1.91)	1.89 (1.94)	1.87 (1.81)	0.983
	Messenger (M (SD))	5.3 (1.51)	5.29 (1.51)	5.32 (1.49)	0.966
	Making New Friends (M (SD))	1.35 (1.89)	1.36 (1.89)	1.3 (1.9)	0.857
	Scheduling (M (SD))	1.91 (2.1)	1.89 (2.11)	2.0 (2.06)	0.652
	Health (M (SD))	1.64 (1.98)	1.63 (1.97)	1.67 (2.03)	0.945
	Zoom Meetings (M (SD))	0.63 (1.46)	0.64 (1.47)	0.61 (1.4)	0.938
	Online Shopping (M (SD))	2.09 (2.17)	2.08 (2.17)	2.13 (2.18)	0.934
	Selling Goods & Services (M (SD))	1.62 (2.08)	1.62 (2.08)	1.61 (2.07)	0.987
	Banking (M (SD))	1.43 (1.91)	1.47 (1.94)	1.24 (1.78)	0.110
	Investment (M (SD))	0.73 (1.4)	0.71 (1.36)	0.81 (1.54)	0.529
	Gaming (M (SD))	4.85 (1.82)	4.84 (1.85)	4.92 (1.67)	0.718
	Watching Videos (M (SD))	5.24 (1.64)	5.22 (1.65)	5.3 (1.6)	0.695
	Listening Music (M (SD))	4.42 (2.07)	4.44 (2.05)	4.32 (2.16)	0.625
	Listening Radio (M (SD))	1.6 (2.06)	1.61 (2.07)	1.58 (2.02)	0.976
	Webtoon (M (SD))	3.3 (2.25)	3.27 (2.25)	3.42 (2.28)	0.519
	Photography (M (SD))	3.46 (2.0)	3.46 (2.02)	3.49 (1.91)	0.967
	Travel (M (SD))	1.69 (1.93)	1.71 (1.94)	1.61 (1.86)	0.652
	Adult Content (M (SD))	0.4 (1.04)	0.4 (1.04)	0.41 (1.06)	0.956
	Gambling (M (SD))	0.38 (1.06)	0.37 (1.04)	0.43 (1.13)	0.570
	News (M (SD))	2.4 (2.14)	2.38 (2.16)	2.47 (2.05)	0.770
	Educational Web Search (M (SD))	3.9 (1.89)	3.91 (1.91)	3.88 (1.82)	0.971
	Hobby Web Search (M (SD))	3.78 (1.97)	3.78 (1.96)	3.81 (2.0)	0.947
	Navigation (M (SD))	2.35 (1.95)	2.34 (1.97)	2.37 (1.88)	0.978
	Online Learning (M (SD))	3.56 (2.23)	3.56 (2.26)	3.55 (2.13)	0.999
	Smartphone Online Video Usage (n (%))	1,805 (96.4%)	1,441 (96.2%)	364 (97.1%)	0.722
	Short Form Platform YouTube (n (%))	920 (49.1%)	740 (49.4%)	180 (48.0%)	0.889
	Short Form Platform TikTok (n (%))	378 (20.2%)	294 (19.6%)	84 (22.4%)	0.489
	Short Form Platform Reels (n (%))	192 (10.3%)	146 (9.7%)	46 (12.3%)	0.355
	Short Form Platform Etc (n (%))	16 (0.9%)	13 (0.9%)	3 (0.8%)	0.992
	Short Form Platform Never (n (%))	299 (16.0%)	248 (16.6%)	51 (13.6%)	0.377
	Short Form Video Usage (M (SD))	1.72 (1.13)	1.69 (1.13)	1.83 (1.13)	0.109

Table A11. All 131 One-Hot Encoded Features (continued): Smartphone Use Cases

Variable Category	Variable	Total Sample (N=1,873)	Training Set (n=1,498)	Test Set (n=375)	p-value
Smartphone Use Cases					
	Mostly Food (n (%))	929 (49.6%)	742 (49.5%)	187 (49.9%)	0.897
	Mostly Sports (n (%))	586 (31.3%)	469 (31.3%)	117 (31.2%)	0.961
	Mostly Fashion/Beauty (n (%))	429 (22.9%)	337 (22.5%)	92 (24.5%)	0.388
	Mostly Gaming (n (%))	770 (41.1%)	616 (41.1%)	154 (41.1%)	0.918
	Mostly Dramas/Variety Show (n (%))	730 (39.0%)	580 (38.7%)	150 (40.0%)	0.642
	Mostly Animation/Comics (n (%))	631 (33.7%)	510 (34.0%)	121 (32.3%)	0.541
	Mostly TV/Entertainment (n (%))	620 (33.1%)	491 (32.8%)	129 (34.4%)	0.548
	Mostly Music/Dance (n (%))	612 (32.7%)	491 (32.8%)	121 (32.3%)	0.869
	Mostly Talk/Streaming (n (%))	563 (30.1%)	446 (29.8%)	117 (31.2%)	0.607
	Mostly Movies (n (%))	537 (28.7%)	424 (28.3%)	113 (30.1%)	0.500
	Mostly Products (n (%))	529 (28.2%)	419 (28.0%)	110 (29.3%)	0.625
	Mostly Current Affairs (n (%))	497 (26.5%)	394 (26.3%)	103 (27.5%)	0.647
	Mostly Lifestyle (n (%))	493 (26.3%)	394 (26.3%)	99 (26.4%)	0.974
	Mostly Edu (n (%))	488 (26.1%)	391 (26.1%)	97 (25.9%)	0.946
	Mostly Kids (n (%))	439 (23.4%)	350 (23.4%)	89 (23.7%)	0.879
	Mostly Vlog (n (%))	1,032 (55.2%)	775 (54.6%)	257 (57.1%)	0.703
	Mostly Other (n (%))	1,870 (99.8%)	1,496 (99.9%)	374 (99.7%)	0.323
Perceived Digital Risk					
	Smartphone Usage Dependence Comparison (M (SD))	2.73 (0.75)	2.72 (0.74)	2.74 (0.79)	0.889
	Side Effects on SNS (n (%))	126 (6.7%)	112 (7.5%)	14 (3.7%)	-
	Side Effects on Email (n (%))	30 (1.6%)	24 (1.6%)	6 (1.6%)	-
	Side Effects on Messenger (n (%))	67 (3.6%)	53 (3.5%)	14 (3.7%)	-
	Side Effects on New Friends (n (%))	51 (2.7%)	37 (2.5%)	14 (3.7%)	-
	Side Effects on Scheduling (n (%))	17 (0.9%)	12 (0.8%)	5 (1.3%)	-
	Side Effects on Health (n (%))	10 (0.5%)	10 (0.7%)	0 (0.0%)	-
	Side Effects on Zoom (n (%))	8 (0.4%)	7 (0.5%)	1 (0.3%)	-
	Side Effects on Shopping (n (%))	71 (3.8%)	55 (3.7%)	16 (4.3%)	-
	Side Effects on Selling (n (%))	21 (1.1%)	19 (1.3%)	2 (0.5%)	-
	Side Effects on Banking (n (%))	6 (0.3%)	5 (0.3%)	1 (0.3%)	-
	Side Effects on Investment (n (%))	15 (0.8%)	12 (0.8%)	3 (0.8%)	-
	Side Effects on Gaming (n (%))	774 (41.3%)	607 (40.5%)	167 (44.5%)	0.369

Table A12. All 131 One-Hot Encoded Features (continued): Smartphone Use Cases

Variable Category	Variable	Total Sample (N=1,873)	Training Set (n=1,498)	Test Set (n=375)	p-value
	Side Effects on Watching Videos (n (%))	141 (7.5%)	113 (7.5%)	28 (7.5%)	-
	Side Effects on Listening Music (n (%))	5 (0.3%)	5 (0.3%)	0 (0.0%)	-
	Side Effects on Listening Radio (n (%))	3 (0.2%)	3 (0.2%)	0 (0.0%)	-
	Side Effects on Webtoon (n (%))	48 (2.6%)	36 (2.4%)	12 (3.2%)	-
	Side Effects on Photography (n (%))	3 (0.2%)	2 (0.1%)	1 (0.3%)	-
	Side Effects on Travel (n (%))	2 (0.1%)	2 (0.1%)	0 (0.0%)	-
	Side Effects on X-Rated Content (n (%))	47 (2.5%)	35 (2.3%)	12 (3.2%)	-
	Side Effects on Gambling Game (n (%))	16 (0.9%)	13 (0.9%)	3 (0.8%)	-
	Side Effects on News (n (%))	6 (0.3%)	6 (0.4%)	0 (0.0%)	-
	Side Effects on Edu (n (%))	4 (0.2%)	4 (0.3%)	0 (0.0%)	-
	Side Effects on Interests (n (%))	1 (0.1%)	1 (0.1%)	0 (0.0%)	-
	Side Effects on Navigation (n (%))	5 (0.3%)	5 (0.3%)	0 (0.0%)	-
	Side Effects on Distance Class (n (%))	10 (0.5%)	5 (0.3%)	5 (1.3%)	-
	Excessive Smartphone Usage (M (SD))	2.6 (0.71)	2.6 (0.69)	2.59 (0.75)	0.947
	Short Form Video Usage Control Difficulty (M (SD))	1.76 (1.11)	1.74 (1.12)	1.85 (1.09)	0.209
Perceived Digital Competence					
	Necessary Information Access (M (SD))	3.26 (0.65)	3.25 (0.66)	3.29 (0.65)	0.619
	Assess Online Information Reliability (M (SD))	2.98 (0.76)	2.97 (0.76)	3.0 (0.75)	0.791
	Online Social Issue Engagement (M (SD))	2.77 (0.84)	2.76 (0.85)	2.78 (0.82)	0.972
	Digital Content Creation (M (SD))	2.49 (0.99)	2.47 (0.99)	2.57 (0.97)	0.197
	Online Privacy Awareness (M (SD))	2.65 (0.88)	2.64 (0.88)	2.68 (0.86)	0.756
	Use Online Information for Academia/Work (M (SD))	2.79 (0.91)	2.79 (0.93)	2.8 (0.85)	0.981
Smartphone Consequences & Dependence					
	Low Battery Nervousness (M (SD))	2.77 (0.85)	2.76 (0.85)	2.79 (0.84)	0.790
	Smartphone Usage Depression (M (SD))	2.19 (0.84)	2.18 (0.83)	2.22 (0.9)	0.740
	Physical Effects (M (SD))	2.31 (0.88)	2.31 (0.87)	2.33 (0.91)	0.923
	Periodic Check Nervousness (M (SD))	2.58 (0.75)	2.57 (0.75)	2.6 (0.76)	0.836
	Smartphone Usage Sleep Issues (M (SD))	2.24 (0.86)	2.23 (0.85)	2.29 (0.9)	0.539
	Social Isolation (M (SD))	2.09 (0.79)	2.08 (0.78)	2.14 (0.8)	0.494
	Stress Relief Through Smartphone (M (SD))	2.41 (0.84)	2.4 (0.84)	2.42 (0.85)	0.918

Table A13. All 131 One-Hot Encoded Features (continued): Risk, Competence, Consequences, Prevention, Support, Regulation, Satisfaction

Variable Category	Variable	Total Sample (N=1,873)	Training Set (n=1,498)	Test Set (n=375)	p-value
Preventative Education					
	Received Preventive Education (n (%))	589 (31.4%)	466 (31.1%)	123 (32.8%)	0.819
	Awareness of Treatment Options (n (%))	958 (51.1%)	768 (51.3%)	190 (50.7%)	0.979
Intent to Seek Smartphone Education					
	Participation Intention (M (SD))	2.24 (0.72)	2.25 (0.73)	2.2 (0.69)	0.501
Parental Prevention Efforts					
	Complete Restriction (n (%))	1,132 (60.4%)	912 (60.9%)	220 (58.7%)	0.735
	Teaches How to Use the Phone Use (n (%))	811 (43.3%)	652 (43.5%)	159 (42.4%)	0.926
	Restrict Smartphone Apps (n (%))	1,132 (60.4%)	912 (60.9%)	220 (58.7%)	0.735
	Teaches Pros and Cons (n (%))	1,112 (59.4%)	885 (59.1%)	227 (60.5%)	0.877
	Recommends Good Apps (n (%))	825 (44.0%)	650 (43.4%)	175 (46.7%)	0.521
	Uses Good Apps Together (n (%))	555 (29.6%)	439 (29.3%)	116 (30.9%)	0.827
	Plays Good Games Together (n (%))	506 (27.0%)	393 (26.2%)	113 (30.1%)	0.315
	Family Smartphone Rules (n (%))	759 (40.5%)	599 (40.0%)	160 (42.7%)	0.640
Social Support					
	Family Support (M (SD))	3.24 (0.71)	3.23 (0.71)	3.27 (0.70)	0.616
	Friend Support (M (SD))	3.12 (0.68)	3.11 (0.67)	3.13 (0.70)	0.940
	Societal Fairness Perception (M (SD))	2.9 (0.75)	2.91 (0.74)	2.86 (0.76)	0.520
Self-Regulation Assessments					
	Smartphone Usage Avoid While Walking (n (%))	1,196 (63.9%)	949 (63.4%)	247 (65.9%)	0.663
	Smartphone Usage Habits Check (n (%))	508 (27.1%)	408 (27.2%)	100 (26.7%)	0.976
	Smartphone Use History Check (n (%))	398 (21.2%)	311 (20.8%)	87 (23.2%)	0.587
	Digital Detox (n (%))	418 (22.3%)	349 (23.3%)	69 (18.4%)	0.126
	Designated Placement (n (%))	591 (31.6%)	468 (31.2%)	123 (32.8%)	0.845
	Use of Work Mode (n (%))	866 (46.2%)	689 (46.0%)	177 (47.2%)	0.916
	Engaging in Conversation (n (%))	793 (42.3%)	647 (43.2%)	146 (38.9%)	0.328
	Hobby Engagement (n (%))	514 (27.4%)	409 (27.3%)	105 (28.0%)	0.964
Life Satisfaction					
	Relationship Satisfaction (M (SD))	3.27 (0.59)	3.27 (0.60)	3.25 (0.57)	0.798
	Work Satisfaction (M (SD))	2.92 (0.71)	2.92 (0.70)	2.9 (0.75)	0.853
	Leisure Satisfaction (M (SD))	2.86 (0.72)	2.87 (0.72)	2.82 (0.69)	0.384
	Overall Life Satisfaction (M (SD))	3.07 (0.59)	3.06 (0.59)	3.07 (0.62)	0.969

Note. p-values are based on comparisons between the training and test sets when cell sizes > 29. One-way ANOVA was used for continuous variables; Pearson’s chi-square test was used for categorical variables. *p < .05 considered statistically significant.

Table A14. Performance metrics across nested AI/ML models for smartphone overdependence

Model	Name	Algorithm	AUC	Mean Val Loss	Test Loss	# Features
M0	Demographics	RF	0.51	0.69	0.69	5
M1	+Urbanicity	DT	0.57	0.70	0.69	8
M2	+Intent to Seek Smartphone Edu	RF	0.63	0.67	0.67	9
M3	+Preventative Education Experiences	LightGBM	0.63	0.67	0.67	11
M4	+Smartphone Use Cases	RF	0.81	0.58	0.55	59
M5	+Home Environment	LightGBM	0.80	0.59	0.54	66
M6	+Parental Prevention Efforts	XGB	0.82	0.58	0.53	75
M7	+Social Support	RF	0.80	0.59	0.57	78
M8	+Self-Regulation Assessments	XGB	0.82	0.56	0.54	86
M9	+Perceived Digital Competence & Risk	XGB	0.89	0.48	0.47	120
M10	+Life Satisfaction	RF	0.88	0.51	0.47	124
M11	+Smartphone Consequences & Dependence	XGB	0.92	0.45	0.39	131

Note: We compare AUC (area under the receiver operating characteristic curve), mean validation loss, test loss and number of features across models. Algorithms used are Random Forest (RF), Decision Tree (DT), Light Gradient-Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost).

Table A15. Performance metrics between construct-based AI/ML models for smartphone overdependence

Construct	Shorthand	Algorithm	AUC	Mean Val Loss	Test Loss	# Features
Smartphone Consequences & Dependence	Smart CD	LightGBM	0.89	0.50	0.42	7
Perceived Digital Competence & Risk	Perceived DCR	XGB	0.84	0.52	0.49	34
Smartphone Use Cases	Use Case	XGB	0.80	0.59	0.54	48
Self-Regulation Assessments	Self-Reg	RF	0.64	0.67	0.66	8
Parental Prevention Efforts	Par Prev	XGB	0.62	0.68	0.67	9
Intent to Seek Smartphone Edu	Intent Edu	LogReg	0.61	0.67	0.67	1
Urbanicity	Urb	LogReg	0.58	0.69	0.69	3
Home Environment	Home Envir	LogReg	0.56	0.70	0.69	8
Preventative Education Experiences	Prev Edu	DT	0.55	0.69	0.69	2
Life Satisfaction	Life Sat	RF	0.54	0.69	0.69	4
Social Support	SoSu	RF	0.53	0.70	0.69	3
Demographics	Demo	RF	0.51	0.69	0.69	5

Note: We compare AUC (area under the receiver operating characteristic curve), mean validation loss, test loss and number of features across models. Algorithms used are Random Forest (RF), Decision Tree (DT), Light Gradient-Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), and Logistic Regression (LogReg).

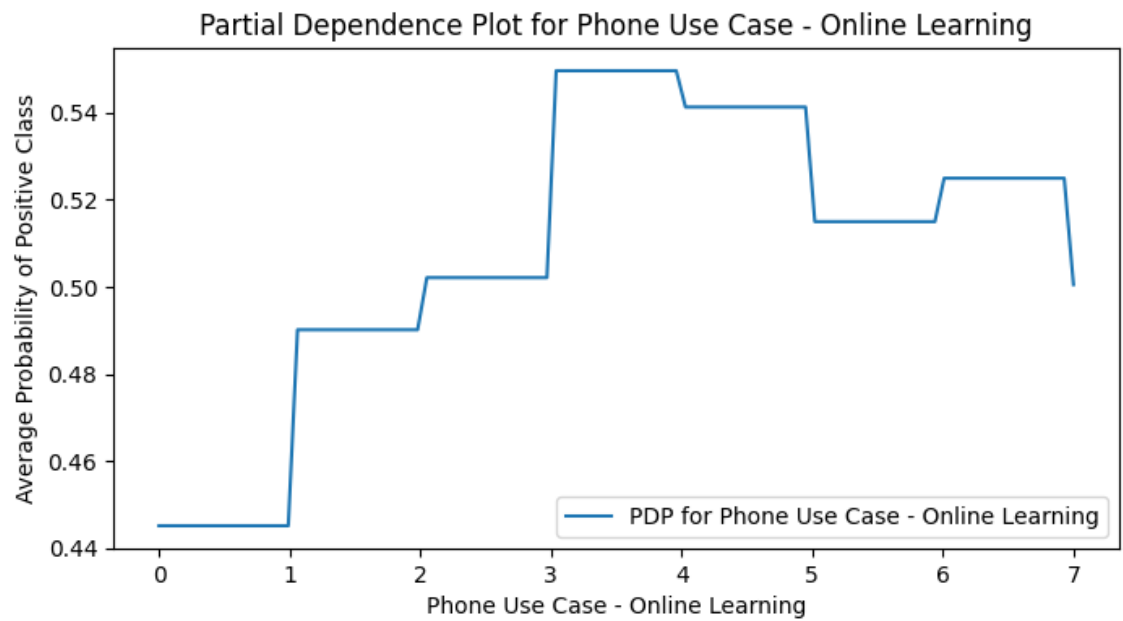


Figure A1. PDP plot of Webtoon in the M4 (+Smartphone Use Cases) model.

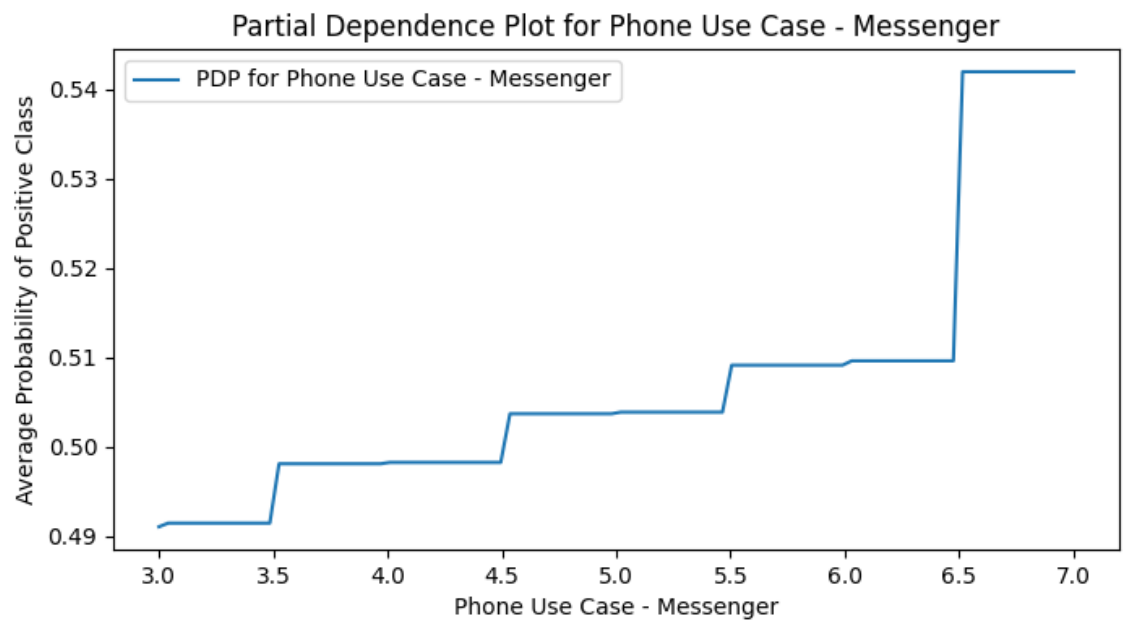


Figure A2. PDP plot of Messenger in the M4 (+Smartphone Use Cases) model.

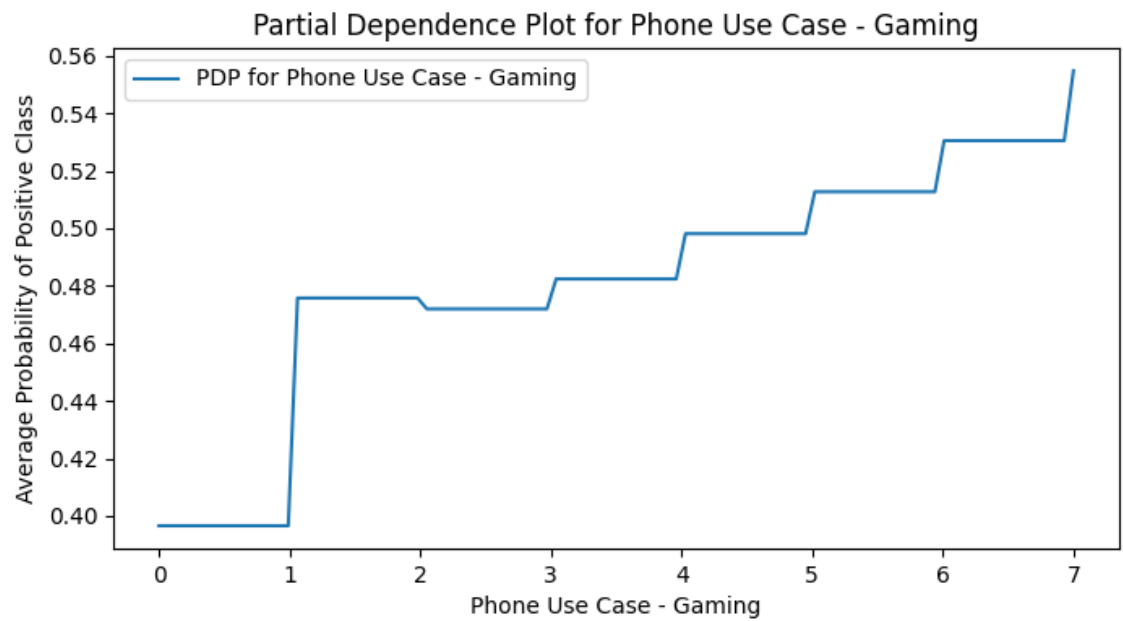


Figure A3. PDP plot of Scheduling in the M4 (+Smartphone Use Cases) model.

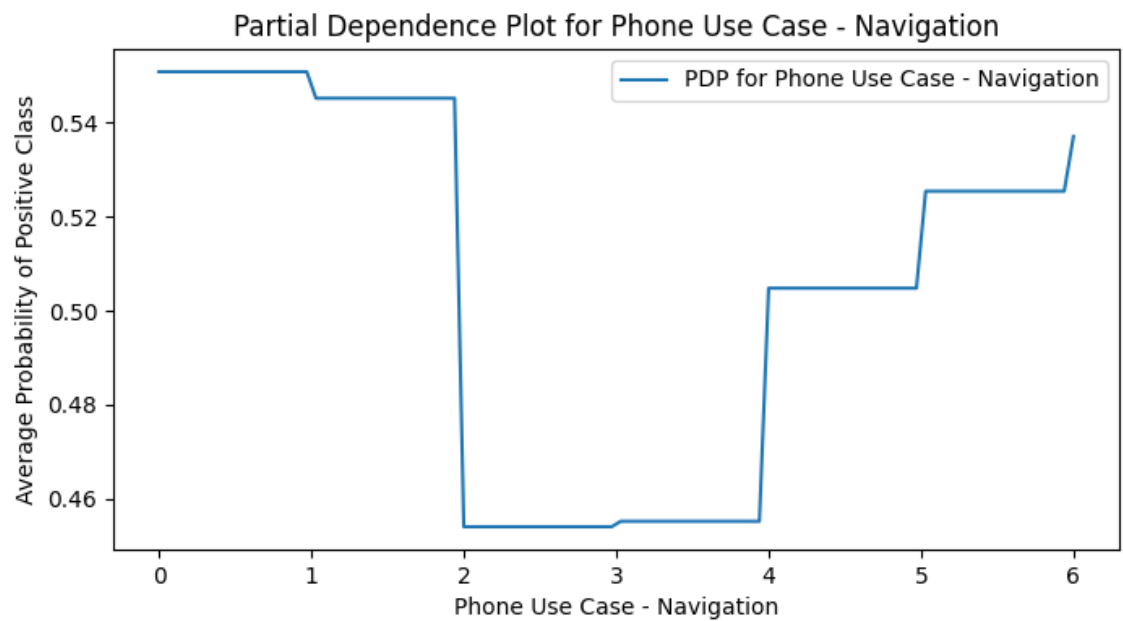


Figure A4. PDP plot of Online Learning in the M4 (+Smartphone Use Cases) model.

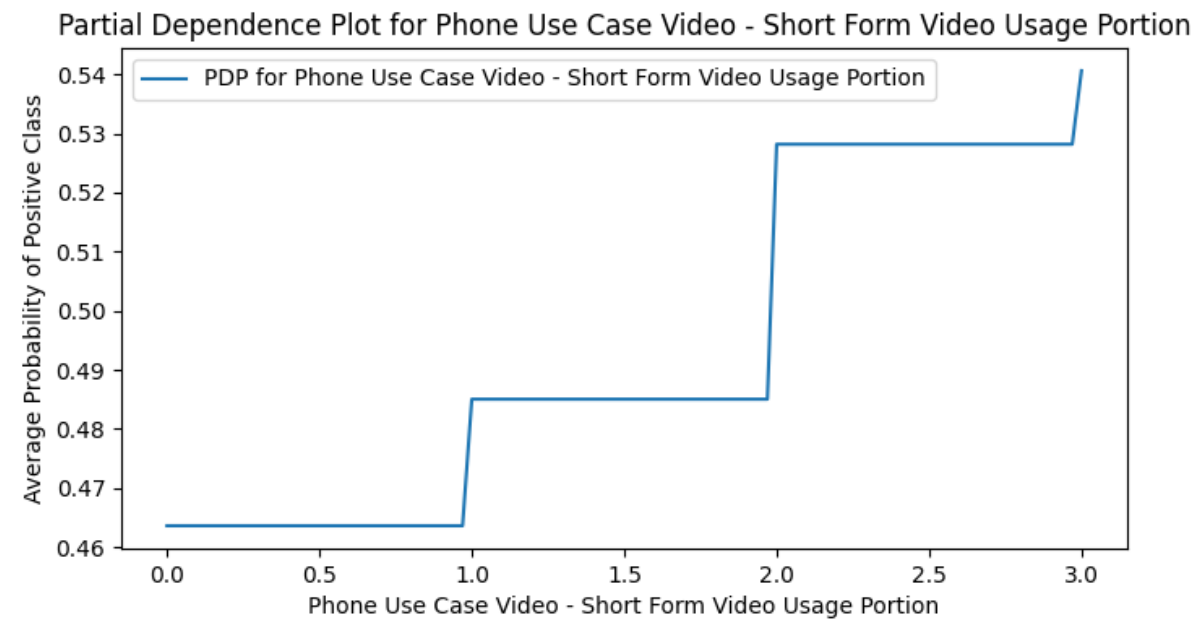


Figure A5. PDP plot of Online Shopping in the M4 (+Smartphone Use Cases) model.

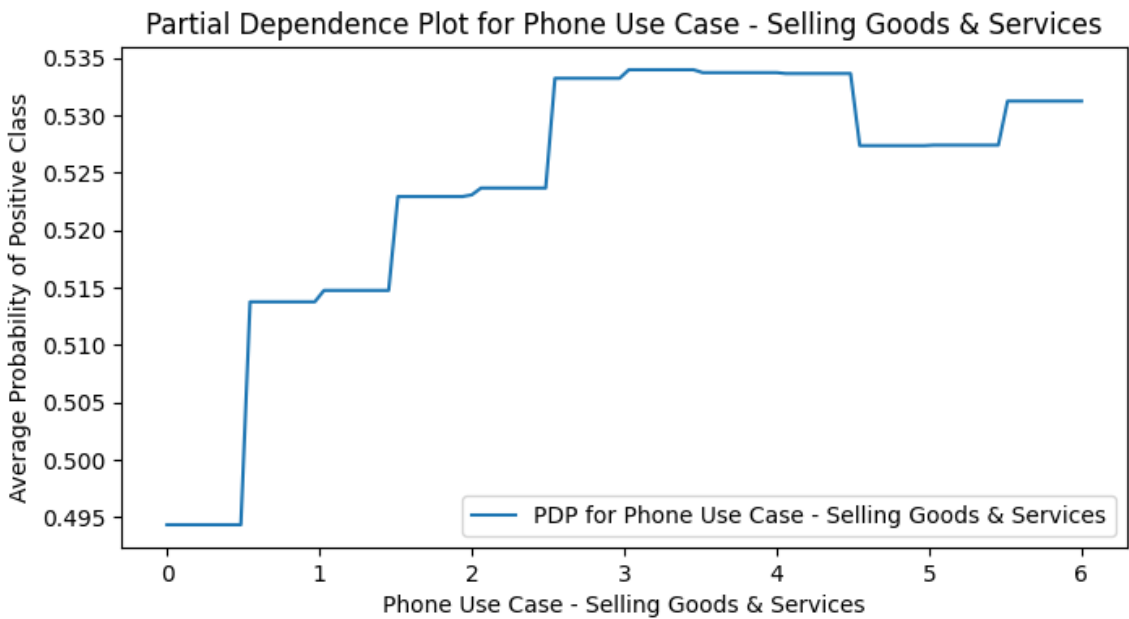


Figure A6. PDP plot of Selling Goods & Services in the M4 (+Smartphone Use Cases) model.

Partial Dependence Plot for Smartphone_Consequences_-_Periodic_Check_Nervousness

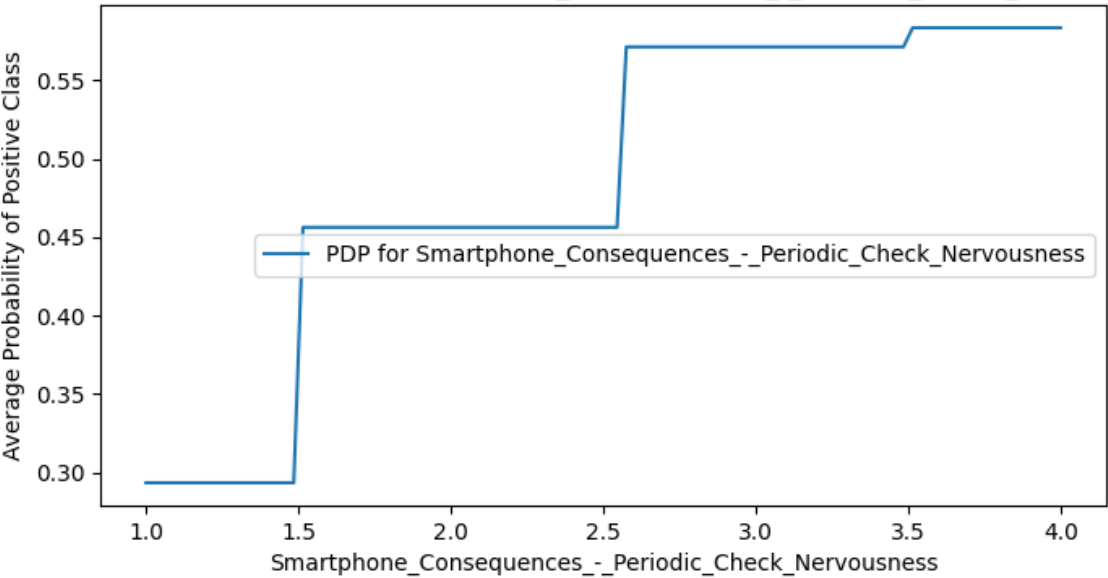


Figure A7. PDP plot of Depression in the Smart CD model.

Partial Dependence Plot for Smartphone_Consequences_-_Sleep_Issues

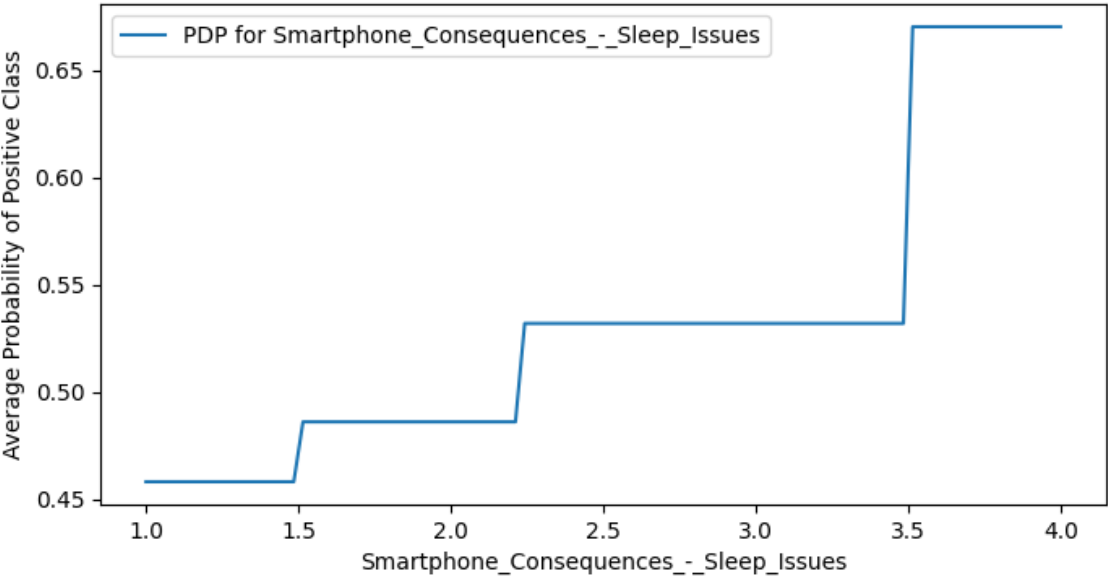


Figure A8. PDP plot of Sleep Issues in the Smart CD model.

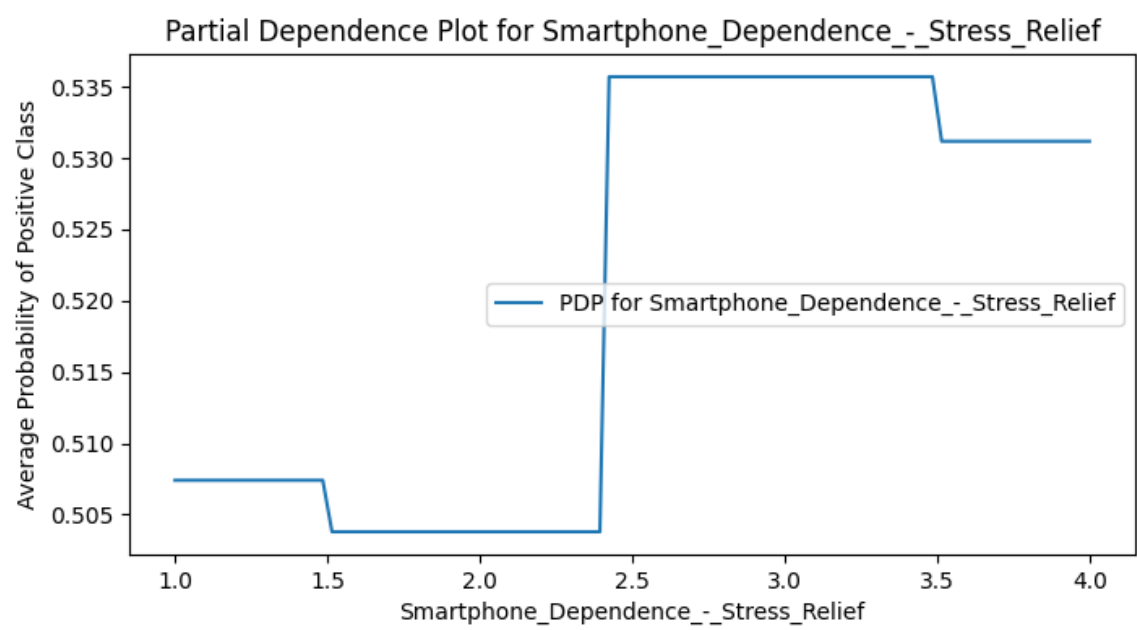


Figure A9. PDP plot of Stress Relief in the Smart CD model.

Partial Dependence Plot for Perceived Phone Issues - Smartphone Usage Dependence Comparison

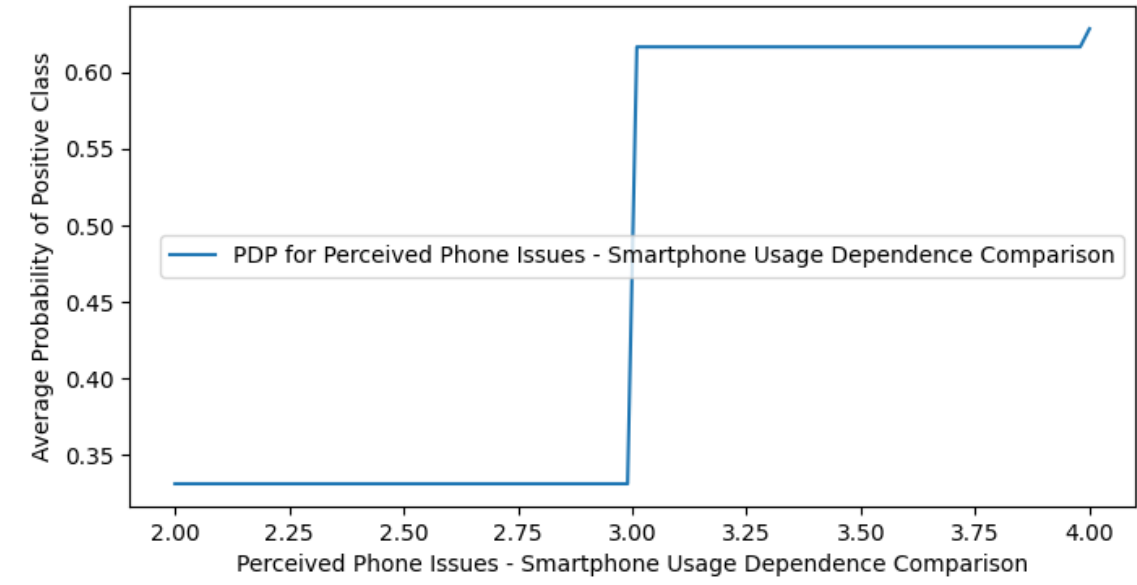


Figure A10. PDP plot of Usage Dependence in the Perceived DCR model.

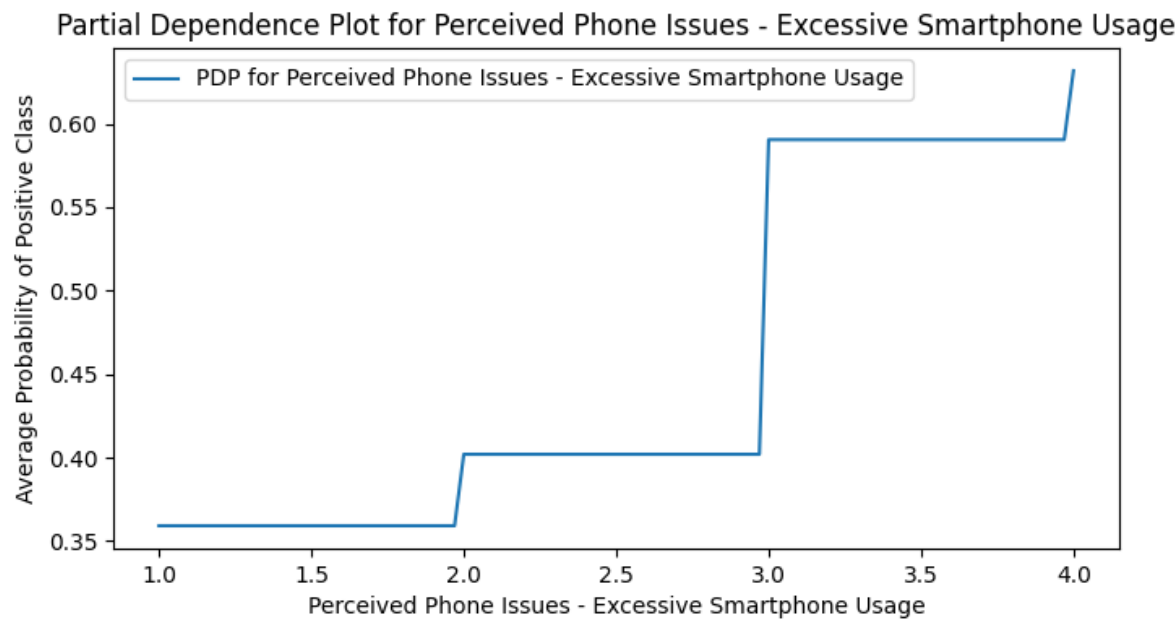


Figure A11. PDP plot of Excessive Usage in the Perceived DCR model.

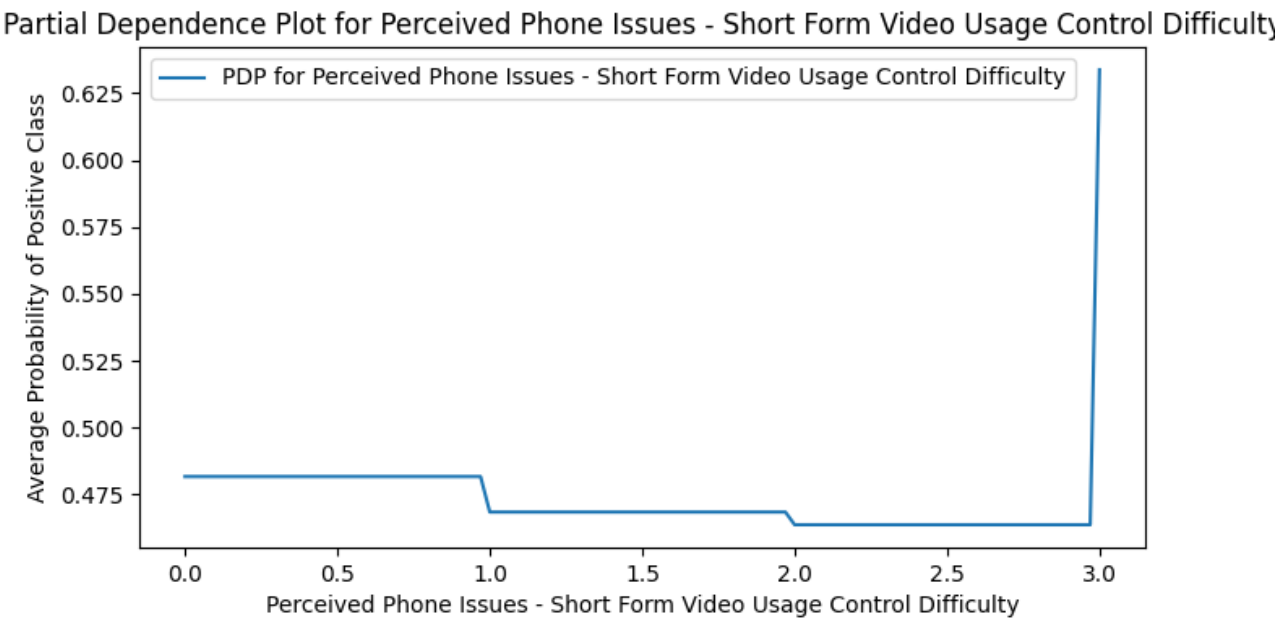


Figure A12. PDP plot of Short Form Usage Control in the Perceived DCR model.

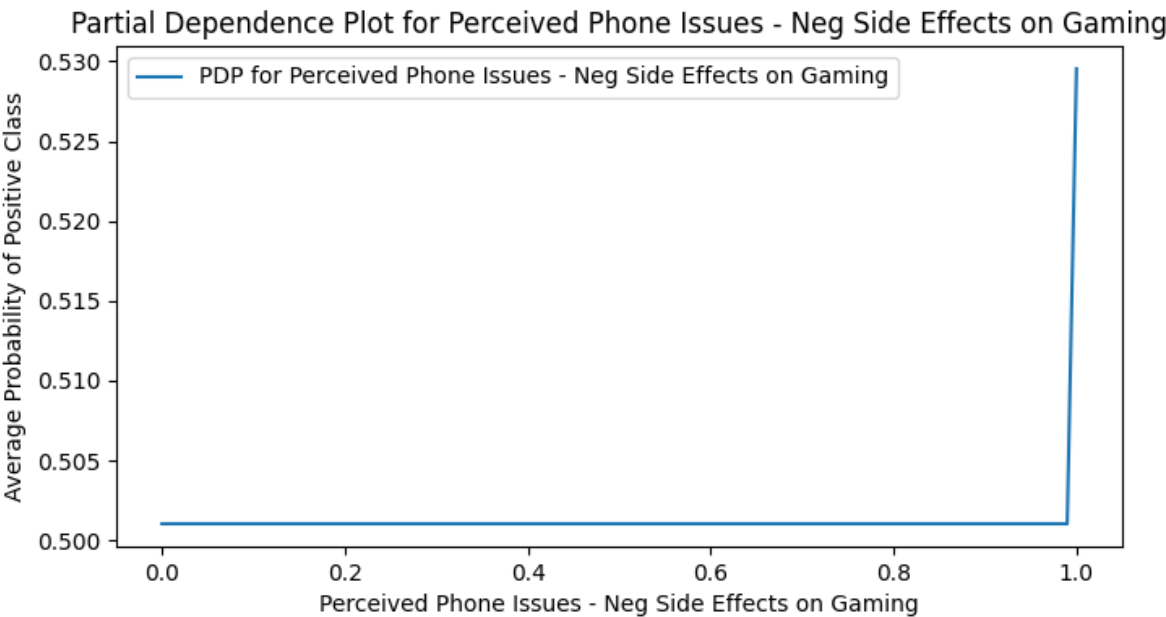


Figure A13. PDP plot of Neg Side Effects on Gaming in the Perceived DCR model.

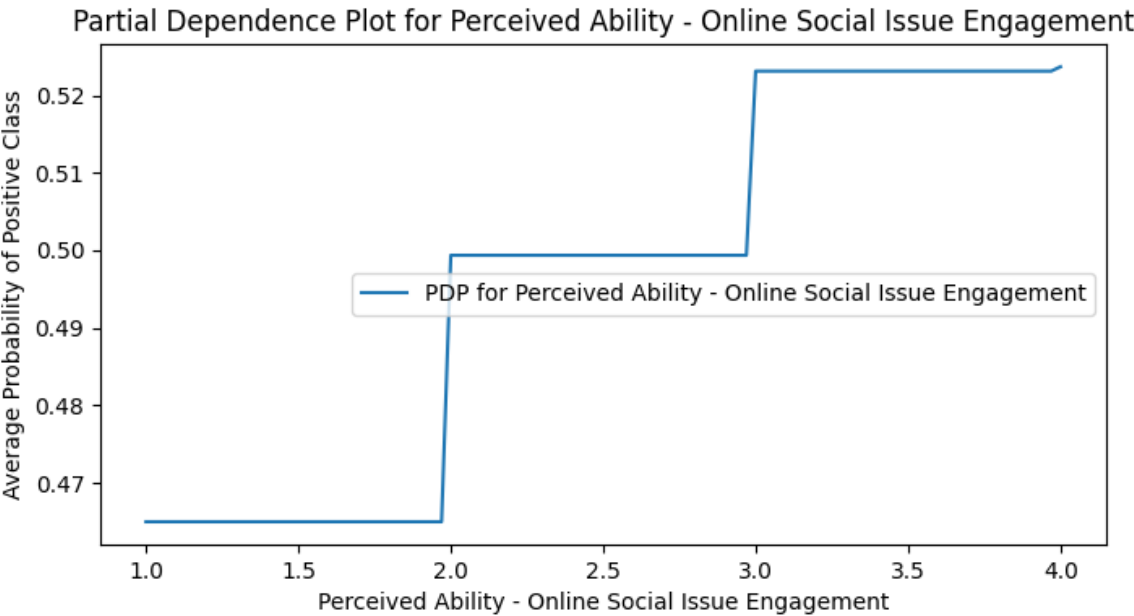


Figure A14. PDP plot of Online Social Issue Engagement in the Perceived DCR model.

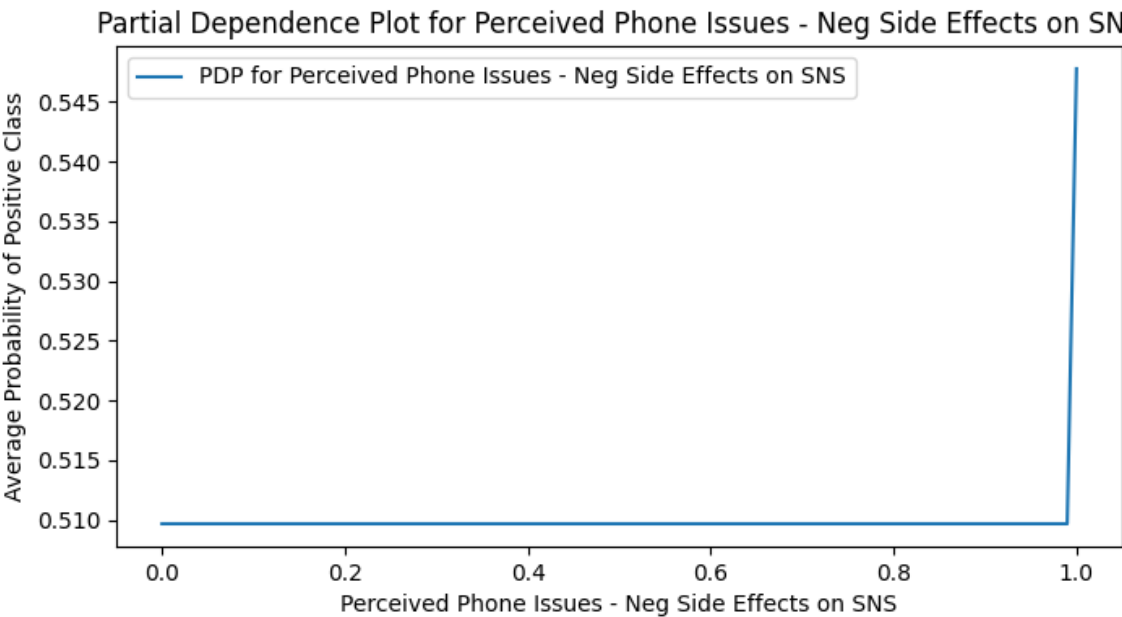


Figure A15. PDP plot of Neg Side Effects on SNS in the Perceived DCR model.

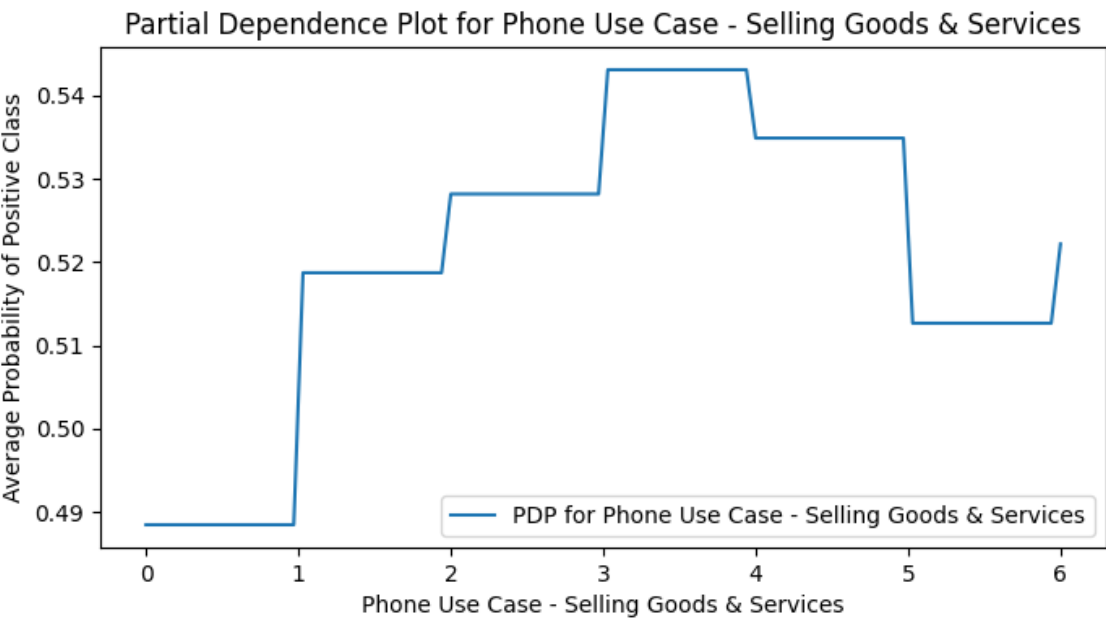


Figure A16. PDP plot of Selling Goods & Services in the Use Case Only model.

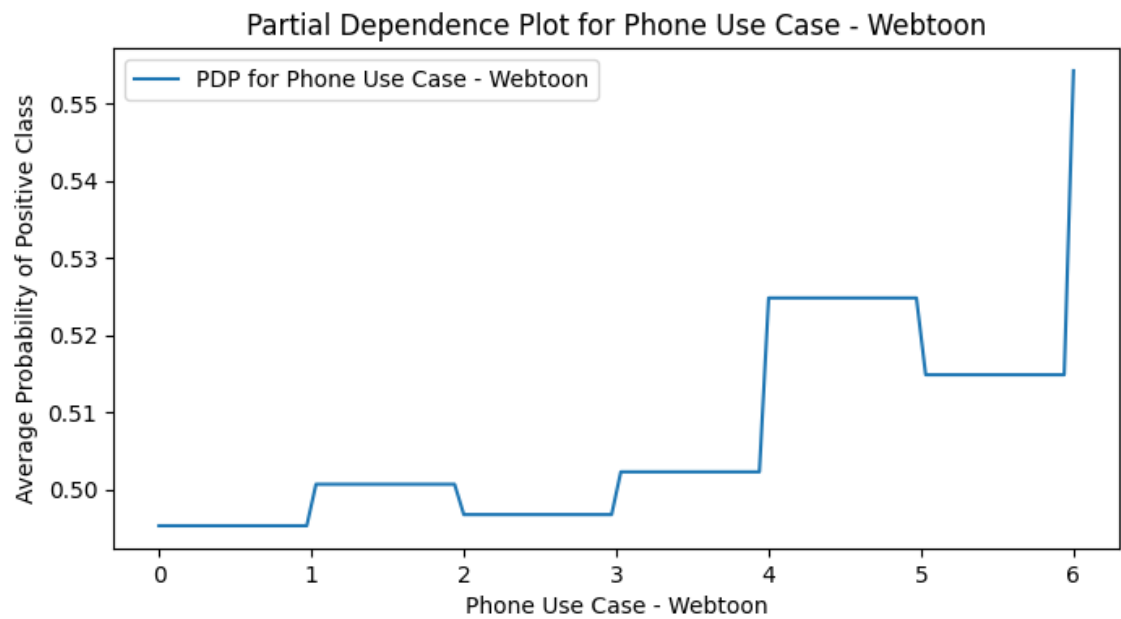


Figure A17. PDP plot of Webtoon in the Use Case Only model.

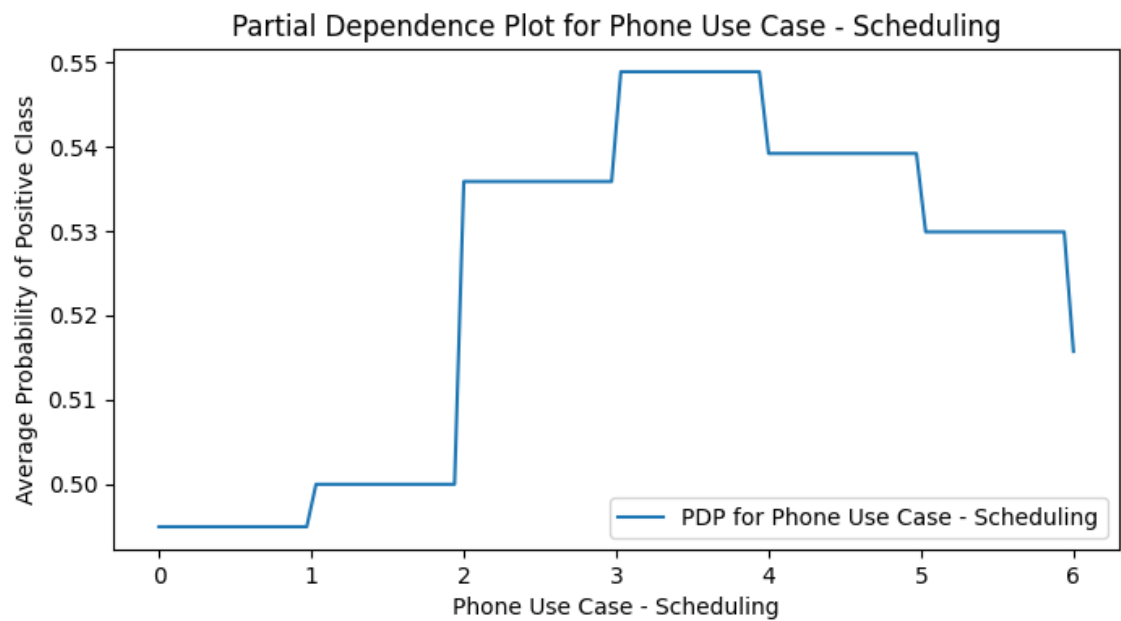


Figure A18. PDP plot of Scheduling in the Use Case Only model.

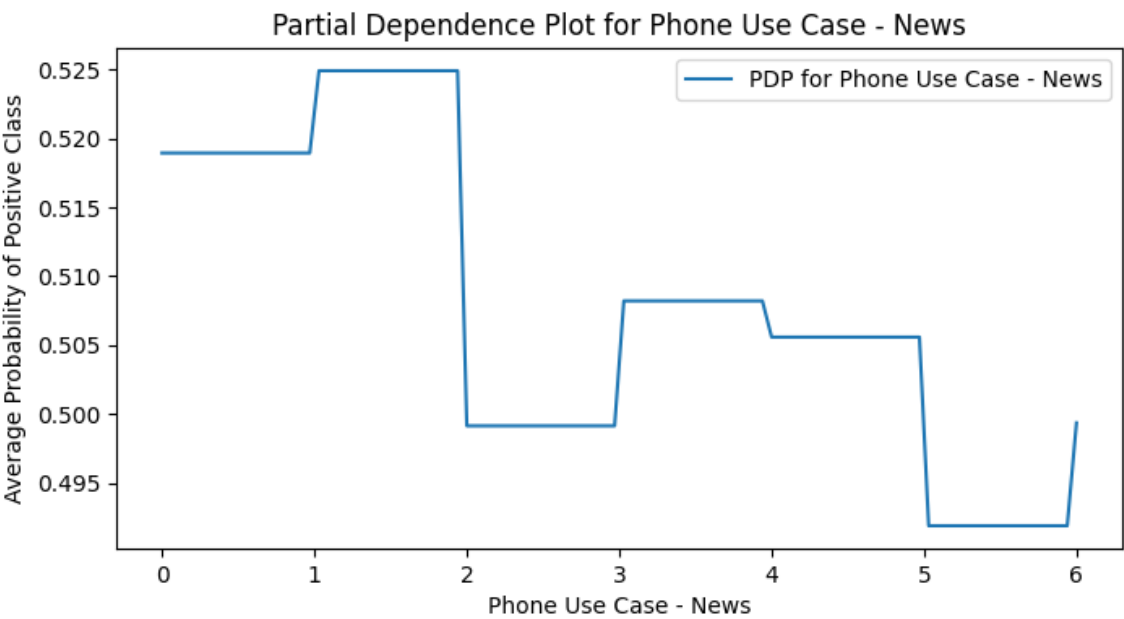


Figure A19. PDP plot of News in the Use Case Only model.

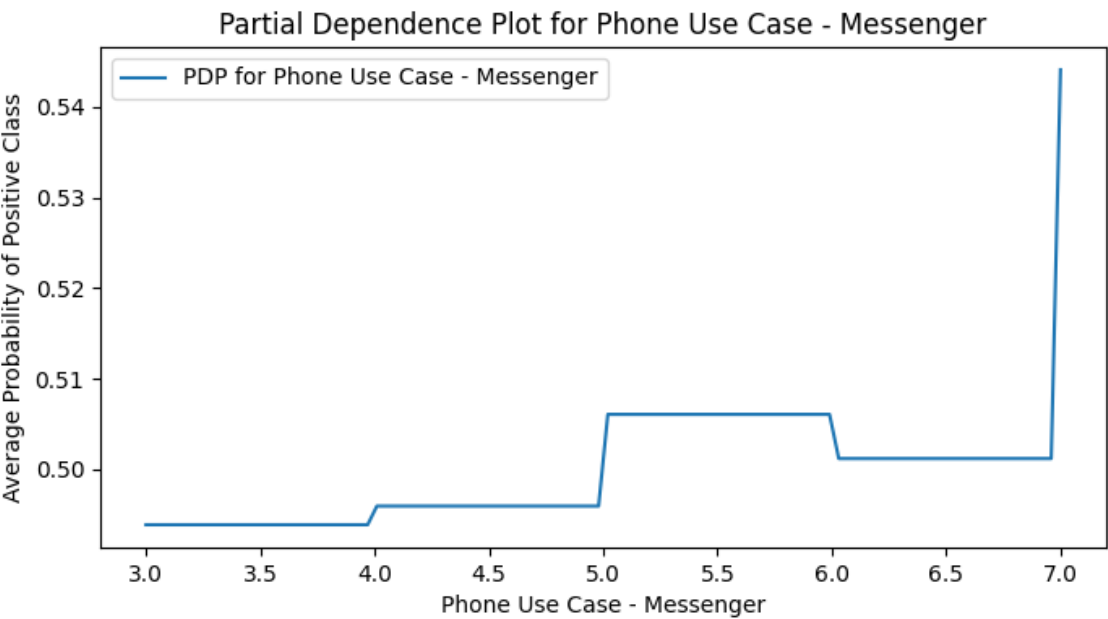


Figure A20. PDP plot of Messenger in the Use Case Only model.

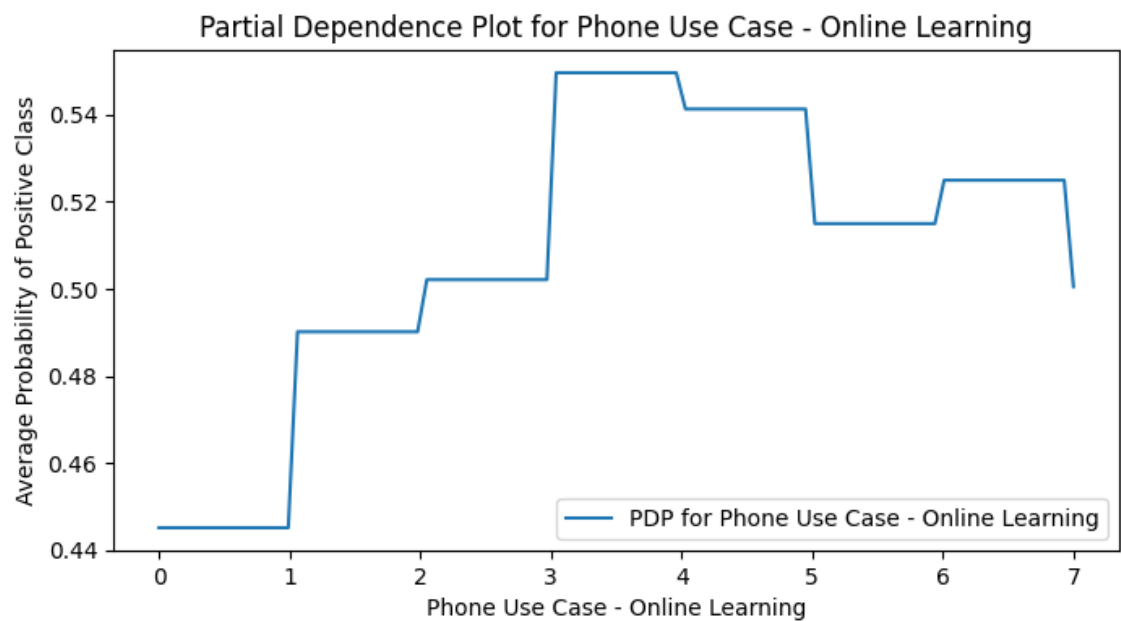


Figure A21. PDP plot of Online Learning in the Use Case Only model.

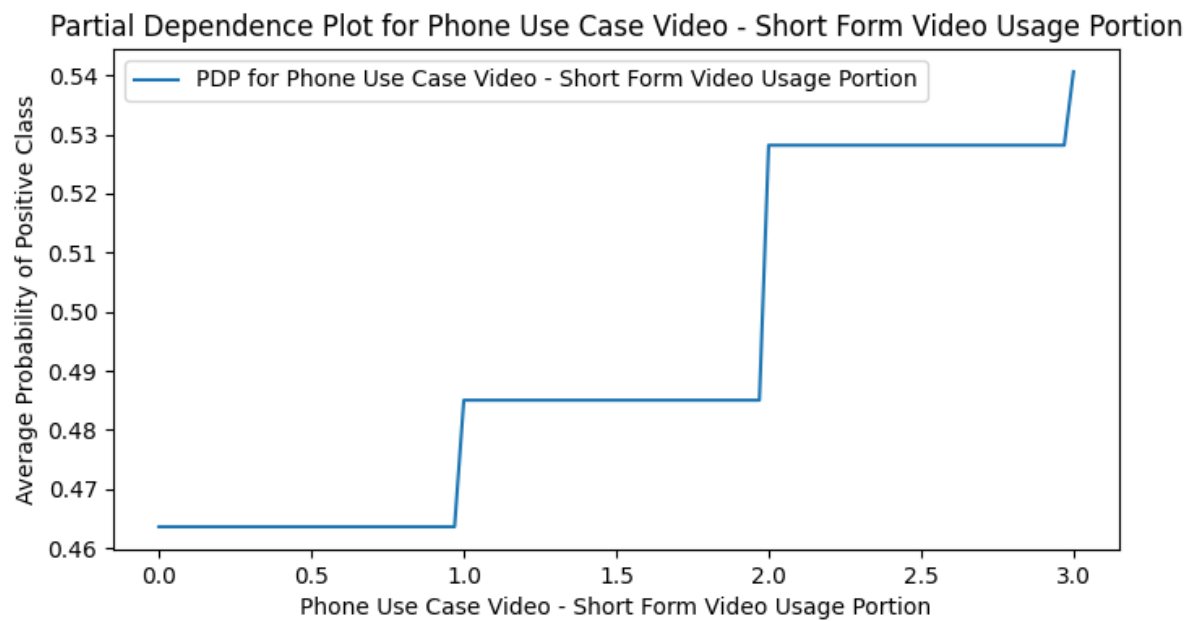


Figure A22. PDP plot of Short Form Video Usage Portion in the Use Case Only model.

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