Prevalence Of Excessive Social Media Use and Its Relationship to Depression and Self-esteem

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Declaration

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Signature: …Jiawei…Lin…………. Date: ……13/06/2023……………………….

Abstract

This study aimed to replicate and expand upon previous research by Bányai et al. (2017) to investigate the relationship between excessive social media use and mental health outcomes in adolescents. Given the high prevalence of depression in Australia and its significant impact on healthcare costs and productivity, understanding the relationship between social media engagement and mental health is crucial. The study utilised survey data from 6,018 Hungarian adolescents. The survey contained questionnaires on the Bergen Social Media Addiction Scale (BSMAS), Centre for Epidemiological Studies Depression (CES-D) scale, and Rosenberg Self-Esteem Scale (RSES). The authors employed Confirmatory Factor Analysis (CFA) to check the validity of the BSMAS and Latent Profile Analysis (LPA) to identify an 'at-risk' group with high BSMAS scores. The results concluded that the BSMAS is a valid scale to measure social media addiction and the 'at-risk' group was associated with lower self-esteem, higher depression symptoms, and excessive social media use. Subsequently, this study expanded upon the original study and employed Structural Equation Modelling (SEM) to examine whether these associations were attributable to the direct influence of BSMAS or the contribution of other unobserved variables. The results indicated that while BSMAS had a direct influence on CES-D, it did not directly influence RSES, suggesting that other unobserved variables might have influenced the association between the 'at-risk' group and low self-esteem. Further research was needed to identify these underlying variables.

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Executive Summary

This study aimed at investigating the link between excessive social media use and mental health outcomes in adolescents, building upon previous research by Bányai et al. (2017). The study utilised survey data from 6,018 Hungarian adolescents and employed various statistical analyses to examine the relationships between social media addiction, depression, and self-esteem.

The motivation for this study stems from the high prevalence of depression in Australia and its significant impact on healthcare costs and productivity. Understanding the association between social media use and mental health is crucial for addressing these concerns effectively.

The authors utilised the Bergen Social Media Addiction Scale (BSMAS), the Centre for Epidemiological Studies Depression (CES-D) scale, and the Rosenberg Self-Esteem Scale (RSES) in their survey. Confirmatory Factor Analysis (CFA) was employed to validate the BSMAS, confirming its reliability as a measure of social media addiction. Additionally, Latent Profile Analysis (LPA) was used to identify an 'at-risk' group characterised by high BSMAS scores. The results of the study indicated that the 'at-risk' group, exhibiting excessive social media use, was associated with lower self-esteem and higher depression symptoms. However, the authors did not investigate whether those associations were due to the direct influence of BSMAS or the contribution of other unobserved variables that were not captured by the survey.

As a result, this study extended the original authors' study and employed Structural Equation Modelling (SEM) to examine whether the observed associations were directly attributable to the BSMAS or influenced by other unobserved variables. The findings from the SEM analysis revealed that while the BSMAS had a direct influence on depression symptoms (CES-D), it did not have a direct influence on self-esteem (RSES). This suggests that other underlying variables, not captured by the survey, might be influencing the association between the 'at-risk' group and low self-esteem. Further research is required to identify and understand these unobserved variables.

Chapter 1 Introduction

To date, Australia has shown a high prevalence of depression, affecting approximately 1 in 6 individuals over their lifetime and 1 in 4 individuals before the age of 20 (Healthdirect.gov.au 2023). This alarming statistic was accompanied by significant healthcare costs and reduced productivity in the workforce (Workplacementalhealth 2018). In fact, in 2021, the Australian government allocated approximately 216 million dollars for antidepressant prescription drugs, underscoring the urgency of identifying contributing factors and implementing effective interventions (Welfare 2023).

One area of interest in understanding mental health was the impact of social media usage, particularly among young people who heavily engaged with these platforms, spending an average of two and a half hours per day on social media (Braghieri, Levy and Makarin 2022). Excessive use of social media has been associated with poor mental health in adolescence, including depression, anxiety, and low self-esteem (Andreassen, Pallesen and Griffiths 2017; Sujarwoto, Saputri and Yumarni 2023; Wegmann, Stodt and Brand 2015; Beeres et al. 2021). Given the significant influence of social media and the amount of time young individuals spend on it, it has become crucial to alleviate the adverse effects of excessive social media usage. Hence, it is essential to gain profound insights into its potential impact and develop targeted interventions. This can be accomplished by examining the relationship between social media usage and mental health concerns, specifically focusing on depression and self-esteem.

This study aims to replicate and extend the research article by Bányai et al. (2017) titled "*Problematic Social Media Use: Results from a Large-Scale Nationally Representative Adolescent Sample*." The study conducted by Bányai et al. (2017) investigated the prevalence of excessive social media use among Hungarian adolescents and its relationship to symptoms of depression and self-esteem. The authors utilised survey data from the European School Survey Project on Alcohol and Other Drugs (ESPAD) with a sample of 6,018 Hungarian adolescents, which was representative of the national population. Bányai et al. (2017) extended the survey by incorporating additional questionnaires. These included the Bergen Social Media Addiction Scale (BSMAS) to measure excessive social media use, the Centre for Epidemiological Studies Depression (CES-D) scale to assess the level of depression symptoms, and the Rosenberg Self-Esteem Scale (RSES) to evaluate the level of self-esteem. To ensure the validity of the BSMAS, Confirmatory Factor Analysis (CFA) was utilised. Bányai et al. (2017) also employed Latent Profile Analysis (LPA) to categorise individuals into different groups based on their BSMAS scores and examine the associations with CES-D and RSES. The study found that 4.5% of the adolescents belonged to the at-risk group, where the average BSMAS score was above 3 out of 5, which indicated low self-esteem, high levels of depression symptoms, and elevated social media use.

While the findings of Bányai et al. (2017) study were important and provided insights into the effects of excessive social media use, further research was necessary to examine whether excessive social media use directly influences depression and self-esteem among adolescents or if it is influenced by a combination of other factors. This was important because previous research had suggested an association between excessive social media use and negative mental health outcomes, but the specific nature of these associations remained incompletely understood (Braghieri, Levy and Makarin 2022; Wilson and McDarby 2023).

Therefore, while Bányai et al. (2017) employed Latent Profile Analysis (LPA) to categorise individuals into different groups based on their BSMAS scores and find the associations with CES-D and RSES, these associations may not have implied direct causation but rather reflected a combination of other unobserved factors due to classification limitations. Thus, in order to build upon Bányai's study and further explore the existence of a direct relationship between the two latent constructs, Structural Equation Modelling (SEM) was utilised. SEM is a statistical technique that expanded upon the general linear framework by considering not only observed variables but also latent variables (Amini and Alimohammadlou 2021). In the SEM framework, both confirmatory factor analysis (CFA) and path analysis were incorporated (Fan et al. 2016). While path analysis primarily focused on examining direct relationships between variables, SEM surpassed path analysis by integrating latent variables through CFA and assessing both direct and indirect effects (Fan et al. 2016). Thus, in this particular study, SEM was utilised to compare the relationships between BSMAS and CES-D, as well as BSMAS and RSES, providing a more comprehensive analysis of the associations between these constructs.

The findings of this study will contribute to a better understanding of the prevalence and nature of problematic social media use among adolescents. The study also extends the approach to assess the nuances in relationship between problematic social media use with depression and self-esteem in adolescents. This research will make an important contribution to the field of adolescent mental health and assist in the development of effective interventions to promote healthy social media use among adolescents.

Chapter 2 Literature Review

2.1 Problematic Social Media Use

Despite the many benefits of using social media (such as staying connected with friends and family, and having easy access to a variety of information), adolescents who used social media excessively reported more symptoms of mental health problems such as depression, anxiety, and low self-esteem (Gao et al. 2020; Bányai et al. 2017; Beeres et al. 2021). Many studies were conducted to investigate factors associated with mental health problems, with some claiming that social media had negative effects, particularly on young people, while others claimed that it had positive effects, and some claimed that both could coexist (Wilson and McDarby 2023).

According to Lee, Cheung, and Thadani (2012), individuals who excessively used Facebook may face challenges in their work, academic performance, and social relationships. Further research suggests that Facebook could potentially amplify negative comparisons and distorted perceptions among individuals. This was evidenced by the noticeable effects observed among students, who develop beliefs that their peers lead more exciting and fulfilling lives, ultimately causing them to feel inadequate or dissatisfied with their own experiences (Braghieri, Levy and Makarin 2022). Several studies indicated that social media use is positively correlated with symptoms of depression and anxiety (Andreassen et al. 2016; Pantic et al. 2012; Sujarwoto, Saputri and Yumarni 2023; Wegmann, Stodt and Brand 2015), as well as reduction in self-esteem (Malik and Khan 2015; Woods and Scott 2016). In addition, research also showed that exposure to different social media themes could lead to different psychological moods, which could be positive or negative (Popat and Tarrant 2022). For example, when exposed to self-harm content on social media, vulnerable users were at a greater risk of experiencing psychological harm, self-harm, and suicidal thoughts (Arendt, Scherr and Romer 2019). On the other hand, individuals found that social media helped to form and strengthen friendships, with online connections providing a less pressurised way to connect with others (O'Reilly 2020; Kennedy and Lynch 2016). Furthermore, adolescents often valued the number of friends and followers they had online as it boosted their self-esteem (Best et al., 2015). However, they may not have always felt supported by their online friends and considered real-life friendships to be more valuable (Best, Taylor and Manktelow 2015).

From the literature mentioned above, it was observed that although most findings aligned with each other, there were contradictions regarding the relationship between excessive social media use and self-esteem, where the relationship could be either positive or negative. Therefore, more research is needed to replicate and extend these findings in order to better understand the nature of the problem and identify other factors that might have influenced specific mental health outcomes associated with excessive social media use.

2.2 Assessing Prevalence of Problematic Social Media Use

Estimating problematic social media use was challenging due to inconsistent assessment tools and a lack of a clear definition (Bányai et al. 2017). Therefore, to obtain a reliable prevalence rate, it was crucial to employ valid measurement tools. Bányai et al. (2017) employed Confirmatory Factor Analysis (CFA) to validate the BSMAS scale and subsequently employed Latent Profile Analysis (LPA) to assess the prevalence of Hungarian adolescents ‘at-risk’. Additionally, they examined the association between ‘at-risk’ adolescents and their depression levels measured by the CES-D scale, as well as their self-esteem levels measured by the RSES scale, both of which were included in their survey questionnaires.

Research showed that females tended to have a higher prevalence of problematic social media use than males, but studies were imbalanced with an over-representation of women, possibly due to their higher willingness to participate (Andreassen, Pallesen and Griffiths 2017). The study by Bányai et al. (2017) found that approximately 4.5% of participants from the sample of 6,018 were classified as being at-risk. Within this group, the 'withdrawal' and 'tolerance' criteria from the BSMAS showed elevated levels compared to the other dimensions.

The article by Braghieri, Levy, and Makarin (2022) used a quasi-experimental approach to investigate the causal relationship between social media and mental health. They utilised the statistical method known as 'generalized difference-in-differences' to compare the mental health data of U.S. college students before and after the introduction of Facebook. To measure mental health, the authors used clinically validated scales: the

PHQ-9 depression scale (Kroenke, Spitzer and Williams 2001) and the GAD-7 generalised anxiety disorder screener (Spitzer et al. 2006). These scales were known to be highly predictive of medical diagnoses. Braghieri, Levy, and Makarin (2022) found that introducing Facebook to U.S. colleges increased predicted depression and anxiety rates by 2%, translating to a 9% increase for PHQ-9 and a 12% increase for GAD-7 compared to pre-period averages.

Sujarwoto, Saputri, and Yumarni (2023) analysed data from 709 Indonesian university students to explore the relationship between social media addiction and mental health. They used the CES-D and BSMAS scales to measure mental health and employed Poisson regression to assess the association. Logistic regression was also used to estimate depression probability. The study revealed that higher social media addiction scores were linked to poorer mental health. Additionally, Sujarwoto, Saputri, and Yumarni (2023) found that students had a lower likelihood of experiencing mental health issues if they had a good relationship with their parents, while females tended to exhibit higher levels of depression symptoms compared to males, aligning with previous findings by Andreassen, Pallesen, and Griffiths (2017).

Chapter 3 Methodology and Data

This study followed the data cleaning process conducted by Bányai et al. (2017). However, due to a lack of clear data cleaning indications from the original author, the final data sample still contained missing values. Consequently, the data underwent further cleaning. As a result, the analysed results in this study may have varied slightly compared to the author's results. Additionally, these result differences could be attributed to limitations in the R programming software used for replication, as compared to the author's use of Mplus 7.3. However, despite these differences, the overall findings aligned with those of the original author. For a detailed analysis, please refer to Appendix A.

3.1 Data Source

The data used for this study was obtained from the original article by Bányai et al. (2017), published in PLOS One. The original data was derived from the 2015 European School Survey Project on Alcohol and Other Drugs (ESPAD), which targeted Hungarian adolescents aged 16. The authors of this study expanded the survey by including additional questionnaires on the depression scale (CES-D) and self-esteem scale (RSES), as well as internet and social media use. The total sample size for this study consisted of 6,664 participants. The specific data selected from this sample can be found in Appendix B.

The authors of the original study conducted data cleaning to address severe incompleteness or inconsistencies, resulting in a final sample of 6,018 participants, which accounted for approximately 90% of the initial sample size. However, despite following the authors' data cleaning process, there were still missing data present within the sample. As a result, the Latent Profile Analysis using the 'tidyLPA' package in the R software was unable to be conducted. Therefore, in this replicated study, further data cleaning was performed to handle the missing data, resulting in a final sample size of 5,525 participants, representing approximately 83% of the initial sample size. This additional cleaning process introduced slight variations in the data analysis results. However, the overall conclusion remains consistent with the authors' findings.

3.2 Confirmatory Factor Analysis (CFA) on BSMAS

Confirmatory factor analysis (CFA) is a statistical tool that examines the construct validity of a measurement instrument or questionnaires (Jackson, Gillaspy and Purc-Stephenson 2009). In the case of Bányai et al. (2017), CFA was employed to validate the BSMAS, a 6-item questionnaire-based instrument designed to measure addiction to social media. The BSMAS consists of six items that assess the core symptoms of addiction: Salience, Tolerance, Mood Modification, Relapse, Withdrawal Symptoms, and Conflict (Bányai et al. 2017). These symptoms, or questions, are labelled as FB1, FB2, FB3, FB4, FB5, and FB6, respectively in the data, as shown in Appendix C.

To evaluate the fit of the CFA model, the p-value of the chi-square test using maximum likelihood estimation is considered, where a p-value greater than 0.05 indicates a close fit, implying that the model's implied covariance matrix matches the population covariance matrix (Barrett 2007). Additionally, other model fit indices are utilised, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR). To indicate a close fit of the model, CFI and TLI should be greater than 0.90 and 0.95, respectively, while RMSEA and SRMR should be less than 0.08 and 0.01, respectively (Bányai et al. 2017; Hu and Bentler 1999).

3.3 Latent Profile Analysis (LPA) on BSMAS

Latent profile analysis (LPA) is a statistical technique that categorises related individuals based on multivariate continuous data by identifying similarities between motivational variables (Lanza and Cooper 2016). LPA helps to uncover hidden groups that may not be easily observed when only looking at relationships between individual variables (Wang and Hanges 2011). The goal was to determine the optimal number of latent profiles (also referred to as classes or groups) that best represented the given population.

Bányai et al. (2017) utilised LPA to identify groups of adolescents at a high risk of problematic social media use. The analysis was conducted on a full sample of 6,018 individuals, estimating 2 to 4 profiles based on their responses to six items from the BSMAS questionnaire. The items were answered on a 5-point scale, ranging from '1-never' to '5-always'. To determine the appropriate number of profiles, the authors employed various fit measurement indices, including the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and the Sample Size Adjusted Bayesian Information Criteria (SSABIC). A lower value on these indices indicated a better fit of the model. Additionally, the entropy criterion was used to assess the accuracy of classifying individuals into their respective profiles, with a higher entropy indicating a better model fit. The authors also conducted the likelihood-ratio difference test (Lo-Mendell-Rubin Adjusted LRT Test) to compare the fit of the estimated model with alternative models containing different numbers of profiles. A p-value less than 0.05 was considered as evidence that the tested model fit better than the alternative models.

After estimating the latent profiles using the BSMAS questionnaires, the authors investigated each data entry within those latent profiles and compared the BSMAS scores with variables such as weekly internet use, weekly social media use, age, gender, depression scale, and self-esteem scale. It then compared the differences in means of these variables within each profile to assess the proportion or percentage of individuals in the population who exhibited symptoms of problematic use of social media platforms. In this case, the study validated that high BSMAS scores were associated with high weekly internet use, high weekly social media use, higher levels of depressive symptoms, as well as lower levels of self-esteem.

A sensitivity analysis was performed to determine the optimal cut-off threshold for the BSMAS score in identifying individuals who exhibit problematic social media use. The 'at-risk' group, identified through LPA analysis as the high social media addiction group, was used as the 'gold standard' for establishing the cut-off threshold. Individuals classified as 'at-risk' were labelled as '0', while the remaining groups were labelled as '1'. Predictions were then generated for various cut-off points based on the BSMAS scores, ranging from 12 to 23 points. Individuals with BSMAS scores that exceeded the cut-off point were classified as the '0 - at-risk' group. These predictions were subsequently compared with the actual predictions (i.e., the gold standard 'at-risk' group classified using LPA) to calculate sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy using a confusion matrix.

3.4 Structural Equation Modelling (SEM)

The SEM determined the causal relationships between latent constructs (Anderson and Gerbing 1988). Various models, such as linear regression, multivariate regression, path analysis, confirmatory factor analysis, and structural regression, were considered as specific instances of SEM (Lin 2021). SEM integrates measurement and structural models to analyse relationships between observed and latent variables. The measurement model (CFA) establishes links between observed and latent variables, while the structural model explores direct and indirect effects among latent variables (Amini and Alimohammadlou 2021; Anderson and Gerbing 1988). Therefore, this study employed SEM to validate the relationship between the BSMAS factor and the latent factor variables of depression (CES-D) and self-esteem (RSES).

The model's fit was assessed using statistical test indices, including CFI, TLI, RMSEA, and SRMR. A good fit of the model was indicated by CFI and TLI values exceeding 0.90 and 0.95, respectively. Additionally, RMSEA and SRMR values were expected to be below 0.08 and 0.01, respectively (Lin 2021). If the model demonstrated a good fit to the data and the estimated parameters were statistically significant, it could be concluded that the hypothesised relationships between BSMAS, CES-D, and RSES were supported by the data.

Chapter 4 Results

4.1 Descriptive Analysis

The final sample consisted of 5,525 participants who fully completed the questionnaire, with approximately 2,668 (48.28%) of them being male. Figure 4-1 illustrates that females tended to spend more time on social network services (SNS) compared to males, resulting in higher BSMAS scores. Furthermore, Figure 4-1 indicates that females had lower average self-esteem scores and higher depression scores compared to males, which may have been influenced by their higher BSMAS scores.

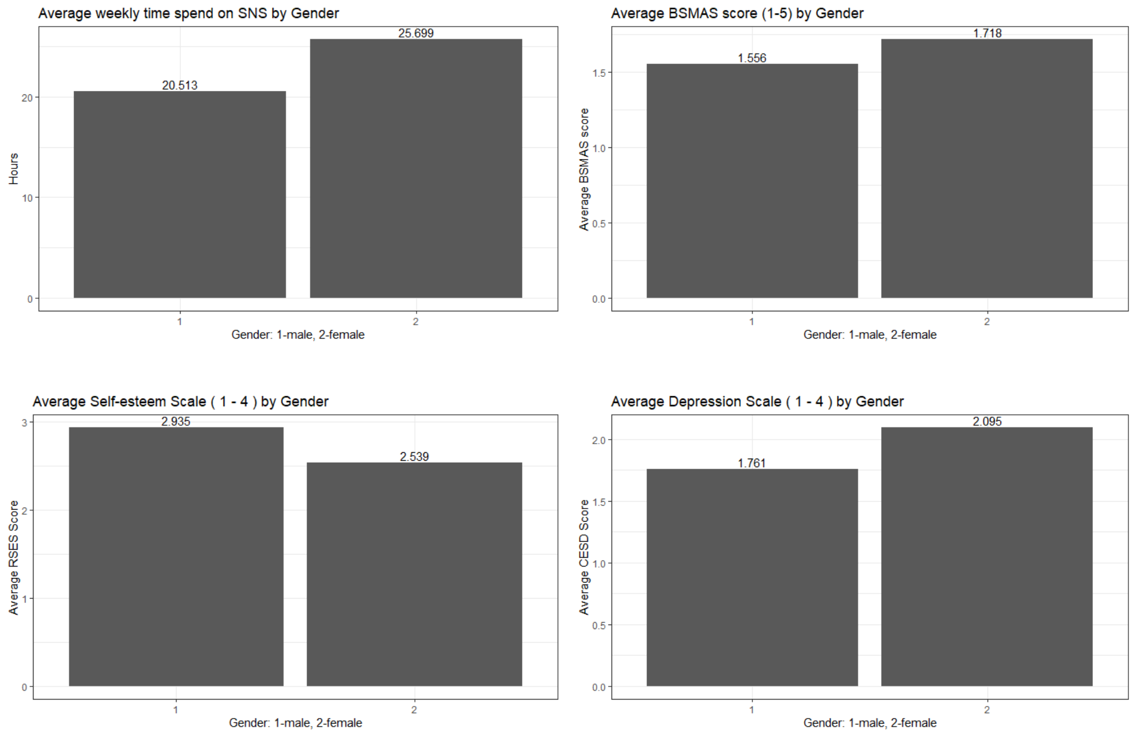

Figure 4-1. The top two graphs showed the average time spent on social network services and the average BSMAS score, categorised by gender. The bottom two graphs display the average self-esteem scale and depression scale scores, also categorised by gender.

4.2 Confirmatory Factor Analysis (CFA) Result

To replicate the authors' CFA and evaluate the validity of the Bergen Social Media Addiction Scale (BSMAS), A one-factor CFA model was applied, utilising six indicator variables for BSMAS: salience, tolerance, mood modification, relapse, withdrawal, and conflict. The majority of model-fit test indices in Table 4-1 closely aligned with the authors' findings, except for the RMSEA test index. In the replicated results, the RMSEA did not indicate a good fit, whereas it did in the authors' results.

Table 4-1. Comparison of CFA Model Fit: Authors Bányai et al. (2017) vs. Replicated Results using Various Test Indices.

Test Indices	**Author's Result**	**Replicated Result**	**Good - Fit Indication**
Degree of Freedom	**15**	**9**	-
Comparative Fit Index (CFI)	0.95	0.952	>0.90 OR >0.95
Tucker-Lewis Index (TLI)	0.0917	0.92	>0.90
Root Mean Square Error of Approx (RMSEA)	**0.073**	**0.108**	<0.05 OR <0.08
Standardized Root Mean Square Residual (SRMR)	0.034	0.034	<0.10
All Loading Factors (FB1, FB2 … FB6)	All Above .50 (0.598 – 0.814)	All Above .05 (0.590 – 0.812)	>.04

Note: The highlighted values indicate the most significant deviations in test results when compared to the findings of Bányai et al. (2017) and this replicated result.

This discrepancy can be attributed to differences in sample size and the use of different software. Additionally, the free R programming software has limited functionality in adjusting CFA parameters compared to the paid software Mplus, which may have resulted in differences in degrees of freedom and subsequently influenced the RMSEA scores. However, despite the disparity in the RMSEA results, the overall findings support the conclusion that the BSMAS remains a valid scale for assessing social media addiction among adolescents.

4.3 Latent Profile Analysis (LPA) Result

To replicate the original study, which categorised individuals into distinct groups based on the six components of the BSMAS, a Latent Profile Analysis (LPA) was conducted to determine the prevalence rate of problematic social media usage. Table 4-2 presents the model fit indices for each LPA model configured with different classes. The variations in the fit values of each index are due to the use of different software. In this case, the replicated results were consistent with those of Bányai et al. (2017), indicating that the optimal model fit was achieved with a three-class model.

Table 4-2. Comparison of LPA Results Based on Fit Indices: Authors Bányai et al. (2017) vs. Replicated Results with Additional Best-fit Model Identified by LPA Algorithm in R software.

Model	LogLik	AIC	BIC	SABIC	Entropy	LMR-LRT test	P
				Author's Result			
2 classes	-43837	87711	87837	87778	0.96	12838	<0.0001
3 classes	-42241	84534	84708	84626	0.94	3140	<0.05
4 classes	-41097	82260	82481	82376	0.95	2251	0.69

Replicated Result

Model	LogLik	AIC	BIC	SABIC	Entropy	BLRT test	P
2 classes	-39381	78801	78927	78866	0.96	12081	0.0099
3 classes	-37869	75789	75961	75879	0.92	3025	0.0099
4 classes	-36835	73737	73955	73850	0.97	831	0.0099

The best-fit model chosen by the LPA algorithm in R

	LogLik	AIC	BIC	SABIC	AWE	CLC	KIC
Selected Model	3 classes	3 classes	3 classes	3 classes	3 classes	3 classes	3 classes

Note: LogLik = Log-likelihood of the data, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SSABIC = sample size adjusted BIC, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test. Additionally R software also provided additional test indices: BLRT = Bootstrap Likelihood Ratio Test, AWE = Approximate Weight of Evidence, CLC = Classification Likelihood Criterion, KIC = Kullback Information Criterion. R does not have the LMR-LRT test, so it has been replaced with the BLRT test for this replicated study.

From Table 4-2, it is evident that the AIC, BIC, and SSABIC values consistently decrease as additional classes are included in the analysis. However, to select a parsimonious model, it is important to choose the model with the fewest classes that still provides an adequate fit, as indicated by lower values on these test criteria (Bányai et al. 2017). Therefore, the three-class model was chosen, even though the four-class model exhibited a better fit. The entropy was the highest for the two-class model, but the entropy of the three-class model was also considered sufficient. The LMR-LRT test conducted by Bányai et al. (2017) supported the acceptance of the three-class solution, and this finding was consistent with the replicated results using the LPA algorithm from the R "tidyLPA" package, which also favoured the three-class model as a better and more parsimonious fit. Although the LMR-LRT test was not available in the R package, other test criteria such as Approximate Weight of Evidence (AWE), Classification Likelihood Criterion (CLC), and Kullback Information Criterion (KIC) indicated that the three-class model exhibited a superior fit. The Bootstrap Likelihood Ratio Test (BLRT) and its p-value indicated significance for all three models, but the three-class model demonstrated a more substantial decrease in the test value compared to the two-class model, relative to the decrease observed from the three-class model to the four-class model. Hence, the replicated conclusion aligns with the findings of Bányai et al. (2017).

Figure 4-2 displayed the distribution of three classes. The first class, labelled 'no-risk,' had the majority of social media users with the lowest BSMAS scores. In the original study by Bányai et al. (2017) 78.3% of users belonged to this group, while the replication found 75.81% falling into the 'no-risk' category. The second class represented users with 'low-risk.' Bányai et al. (2017) classified 17.20% in this group, and the replication showed 16.00%, indicating a close alignment. The third class represented 'at-risk' individuals. Bányai et al. (2017) identified 4.50% as ‘at-risk’, while the replication identified 8.14%. The disparity between the results could be due to different sample sizes and participant compositions, leading to slight variations. Additionally, differences in software or parameters used in the Latent Profile Analysis (LPA) could also contribute to the variations.

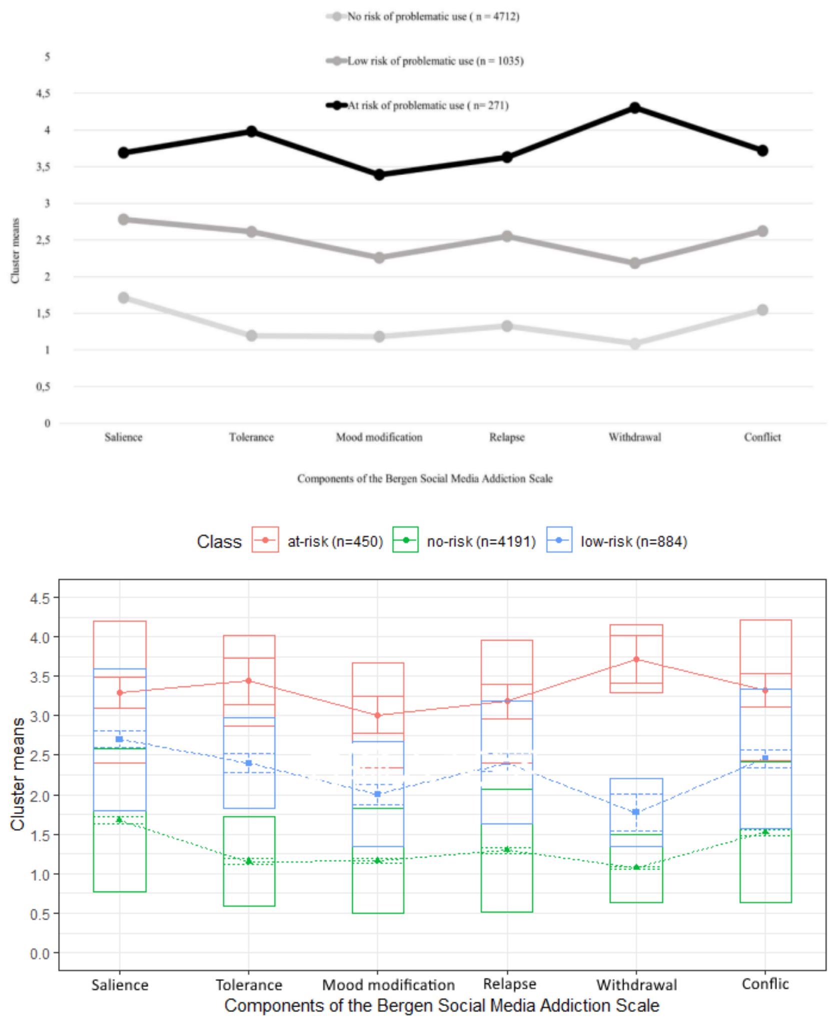

Figure 4-2. Three-Class Model Plot Based on 6 Components of BSMAS - Comparison of Results between Bányai et al. (2017) (top) and Replicated Result (bottom).

Moreover, in Figure 4-2, an individual classified as 'at-risk' exhibited higher levels of 'withdrawal' and 'tolerance' compared to other components. Table 4-3 presents a comparison between the three classified classes using the BSMAS and other variables in the dataset. In this case, the conclusion from Bányai et al. (2017) aligns with this replicated result, with a slight variation in mean value. It indicates that females are more likely to be in the 'at-risk' class, and individuals in the 'at-risk' class tend to spend over 30 hours per week online, as well as exhibiting lower self-esteem and higher depressive symptoms compared to individuals in the other two classes. These findings highlight distinctive traits of the 'at-risk' group and demonstrate the negative impact of excessive social media use on mental health.

Table 4-3. Comparison of Three Latent Classes with Other Variables: Authors Bányai et al. (2017) vs. Replicated Results.

	Author's Result			Replicated Result		
Variables	**No-risk class (n=4721)**	**Low-risk class (n=1035)**	**At-risk class (n=271)**	**No-risk class (n=4191)**	**Low-risk class (n=884)**	**At-risk class (n=450)**
Gender (male %)	50.36	44.51	**41.20**	50.32	40.95	**43.80**
Age (years)	16.60	16.61	**16.69**	16.58	16.54	**16.62**
Weekly Internet Use	22.12	27.11	**31.49**	22.17	26.22	**31.13**
Weekly Social Media Use	21.38	27.68	**33.73**	21.36	27.23	**32.36**
Self-esteem level	2.79	2.54	**2.44**	2.79	2.54	**2.50**
Depression level	1.85	2.16	**2.36**	1.85	2.16	**2.27**

Note: The value above represents the average score of each variable within each class, except for gender which indicates the percentage of males in each class. The variation in the mean value between the authors Bányai et al. (2017) and this replicated result can be attributed to the utilisation of a different sample size, resulting from additional data cleaning procedures outlined in the data source section.

Finally, since there was no clinically diagnosed group of individuals with problematic social media use, Bányai et al. (2017) employed the 'at-risk' class as the 'gold standard' for identifying individuals at risk. They conducted a sensitivity analysis to determine the optimal cut-off threshold for the BSMAS score based on this reference. Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy were calculated for the BSMAS score at various cut-off points. Table 4-4 presented the cut-off points ranging from 16 to 22 (full results can be found in Appendix D with cut-off points ranging from 12 to 23). The study by Bányai et al. (2017) suggested that a BSMAS score of 19 points was the optimal cut-off threshold, while the replicated result indicated that a threshold of 17 points was optimal. The disparity in findings could be attributed to the replicated result classifying a higher percentage (8.14%) of individuals as 'at-risk' compared to the original study, which classified only 4.5% of individuals as 'at-risk' problematic social media users.

According to Table 4-4, the findings of Bányai et al. (2017) indicated that the optimal threshold for classification was set at 19, resulting in a sensitivity of 83% and specificity of 99%. When the study was replicated, the optimal threshold was found to be 17, which increased the sensitivity to 85% while slightly reducing the specificity to 98%. The replicated results demonstrated that only 2% of individuals who were not truly ‘at-risk’ of problematic social media use were mistakenly identified as being ‘at-risk’ by the scale. Conversely, the scale failed to detect 15% of individuals who actually had problematic social media use. At this particular threshold, the positive predictive value (PPV) was 79% and the negative predictive value (NPV) was 99%. To put it simply, 21% of those who tested positive were wrongly identified, while only 1% of those who tested negative were misclassified. Consequently, the screening instrument BSMAS exhibited an overall accuracy of 97%. Raising the threshold would lead to more cases of problematic social media use being overlooked (false negatives), whereas lowering the threshold would result in more social media users being incorrectly labelled as ‘at-risk’.

Table 4-4. Sensitivity Analysis for Suggested Cut-off Points based on 'At-Risk' Group from Latent Profile Analysis: Comparison of Results between Bányai et al. (2017) and Replicated Results.

Cut-off points	True positive	True negative	False positive	False negative	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)
Author's Result									
16	240	5141	386	3	99	93	38	100	93
17	232	5249	278	9	96	95	45	100	95
18	219	5340	188	23	90	97	54	100	96
19	**199**	**5458**	**74**	**40**	**83**	**99**	**73**	**99**	**98**
20	177	5503	29	64	73	99	86	99	98
21	156	5517	17	85	65	100	90	98	98
22	126	5527	8	114	53	100	94	98	98
Replicated Result									
16	411	4890	185	39	91	96	69	99	96
17	**383**	**4972**	**103**	**67**	**85**	**98**	**79**	**99**	**97**
18	340	5022	53	110	76	99	87	98	97
19	**236**	**5047**	**28**	**214**	**52**	**99**	**89**	**96**	**96**
20	191	5069	6	259	42	100	97	95	95
21	163	5073	2	287	36	100	99	95	95
22	129	5074	1	321	29	100	99	94	94

Note: Bold and coloured cut-off points represent a balance between sensitivity and specificity scores, aiming for the highest accuracy.

4.4 Structural Equation Modelling (SEM) Result

So far, Bányai et al. (2017) had used CFA and LPA to validate the BSMAS and had classified adolescent individuals into three classes, examining the association of the 'at-risk' class with other variables as shown in Table 4-3. The study had found that the 'at-risk' class was associated with lower self-esteem and higher depression symptoms. However, it did not determine whether these associations were directly influenced by the BSMAS or if they were influenced by other unobserved variables. To address this limitation, the replicated study had expanded on the work of Bányai et al. (2017) by employing structural equation modelling (SEM), which incorporated both CFA and path analysis. This approach allowed for a more comprehensive analysis of the relationships among the latent constructs. Specifically, the replicated study had examined whether there were direct relationships between BSMAS and CES-D, as well as between BSMAS and RSES. The results of the SEM model fit were presented in Table 4-5 and Table 4-6.

Table 4-5. SEM Test Indices Result for BSMAS against CES-D and Regression Estimates.

BSMAS vs CES-D		
Test Indices	**Fit value**	**Good - Fit Indication**
Comparative Fit Index (CFI)	0.93	>0.90 OR >0.95
Tucker-Lewis Index (TLI)	0.91	>0.90
Root Mean Square Error of Approx (RMSEA)	0.08	<0.05 OR <0.08
Standardized Root Mean Square Residual (SRMR)	0.047	<0.10

Regressions: BSMAS vs CES-D						
	Estimate	**Std.Err**	**z-value**	**P(>|z|)**	**Std.lv**	**Std.all**
CESD ~ BSMAS	0.198	0.011	18.019	0.000	0.340	0.340

Note: The test indices consistently indicate that this SEM is a good fit. As a result, the regression output for CESD vs BSMAS from the SEM holds meaningful interpretations, which is why the regression table was provided. In the "lavaan" R package, the "std.lv" standardised estimates are based on the variances of the continuous latent variables only, while the "Std.all" standardised estimates include both the variances of the observed variables and the latent variables.

Table 4-6. SEM Test Indices Result For BSMAS against RSES.

BSMAS vs RSES		
Test Indices	**Fit value**	**Good - Fit Indication**
Comparative Fit Index (CFI)	0.788	>0.90 OR >0.95
Tucker-Lewis Index (TLI)	0.753	>0.90
Root Mean Square Error of Approx (RMSEA)	0.119	<0.05 OR <0.08
Standardised Root Mean Square Residual (SRMR)	0.083	<0.10

Note: There is no regression estimate table provided because the model was not a good fit.

Based on Table 4-5, the test indices for model fit indicated that the SEM was a good fit, suggesting that BSMAS has a direct influence on the depression scale (CES-D). The regression estimates indicated that a 1-point increase in BSMAS score was associated with a 0.198-point increase in CES-D score. This suggested that higher levels of social media addiction, as measured by BSMAS, were related to higher levels of depression symptoms, as measured by CES-D. However, when fitting the SEM model with BSMAS against the self-esteem scale (RSES), as shown in Table 4-6, The results suggested that the SEM model was not a good fit since the fit indices did not fall within the range of acceptable values for good fit. This suggested that BSMAS did not have a direct influence on self-esteem (RSES). Therefore, the association between the 'at-risk' group and low self-esteem may have been influenced by other factors that were not observed in the available data.

4.5 Discussion

To evaluate the prevalence of problematic social media use accurately and reliably, the psychometric properties of the BSMAS had been examined. The results of the Confirmatory Factor Analysis (CFA) indicated that the BSMAS exhibited satisfactory psychometric properties in terms of its factor structure. This finding suggested that the scale was capable of measuring social media addiction effectively. Additionally, the validity of the BSMAS had been established in other studies conducted by Lin et al. (2017) and Rouleau, Beauregard, and Beaudry (2023). These studies provided further evidence supporting the reliability and effectiveness of the BSMAS in assessing social media addiction among adolescents. By considering the findings from multiple studies, we could be more confident in the validity and usefulness of the BSMAS as a measurement tool for problematic social media use.

The replicated analysis used Latent Profile Analysis on the six components of the BSMAS and had identified three distinct classes of adolescent social media users, with 8.14% of participants classified as being ‘at-risk’. This prevalence rate was higher than the original study, which had classified 4.5% of participants as being ‘at-risk’. It was worth noting that previous studies had also reported a wide range of prevalence rates for problematic social media use, attributed to methodological differences such as convenience sampling, focusing primarily on college students, or having small sample sizes (Balakrishnan and Shamim 2013; Kircaburun et al. 2020; Wilson, Fornasier and White 2010; Zhou and Leung 2012). Despite the discrepancy in the identified prevalence rates of the 'at-risk' group between the original study and the replicated analysis, both fell within the range of appropriate prevalence rates reported in the study by Pontes, Kuss, and Griffiths (2015), which examined the prevalence rates of general addictive Internet use across multiple countries and found a range of 1% to 18.7%. These variations highlighted the importance of considering different factors and methodologies when assessing the prevalence of problematic social media use, and the findings of this replicated study remained in line with the existing literature.

In addition, the ‘at-risk’ group exhibited the lowest levels of self-esteem, the highest level of depressive symptoms, and the highest amount of time spent on internet and social media use, which aligned with previous research (Andreassen et al. 2016; Pantic et al. 2012; Sujarwoto, Saputri and Yumarni 2023; Wegmann, Stodt and Brand 2015; Malik and Khan 2015). Within the at-risk group of individuals with problematic social media use, it was observed that females had a higher inclination towards addictive social media usage, comprising 56.2% of the group. This demographic also reported spending the most time on the internet and social media, resulting in a higher average BSMAS score. These findings align with previous studies that have identified similar gender differences in problematic social media use (Kuss and Griffiths 2011; Andreassen, Pallesen and Griffiths 2017; Žmavc et al. 2022) and problematic internet use (Pontes, Kuss and Griffiths 2015). An example of this is the study conducted by Andreassen, Pallesen, and Griffiths (2017), which discovered that women were more prone to developing addictive behaviours related to social interaction, while men tended to develop problematic use of solitary activities like video gaming.

Furthermore, the findings of the current study indicated that the withdrawal component obtained the highest score within the at-risk group. This highlights the importance of addressing withdrawal symptoms in the development of prevention and intervention programs within a school setting for adolescents who are at risk of problematic social media use. In this replicated study, a cut-off point was established by using the 'at-risk' group identified through LPA as the benchmark for categorising problematic social media users among adolescents in the sample. The suggested cut-off value of 17 points demonstrated optimal sensitivity, specificity, and accuracy, which differed from the original study's cut-off of 19 points. It was important to acknowledge that these cut-off points could not replace clinically validated thresholds, as demonstrated in the study by Luo et al. (2021), which identified a clinical cut-off point of 24 points for the BSMAS. However, they could serve as valuable indicators for identifying potential at-risk candidates within this specific sample of Hungarian adolescents.

Although the original authors found that the 'at-risk' class was associated with lower self-esteem and higher depression symptoms, they did not determine whether these associations were directly influenced by the BSMAS or if they were influenced by other unobserved variables. Therefore, based on the SEM analysis, it was suggested that the BSMAS had a direct influence on the depression scale but not on the self-esteem scale. Specifically, a 1-point increase in BSMAS score was associated with a 0.198-point increase in CES-D score. This result helped explain why many studies had concluded that social media addiction had an impact on the level of depression (Andreassen et al. 2016; Pantic et al. 2012; Wegmann, Stodt and Brand 2015; Sujarwoto, Saputri and Yumarni 2023; Žmavc et al. 2022) but findings regarding the relationship between social media addiction and self-esteem were more diverse. For instance, Andreassen, Pallesen, and Griffiths (2017) demonstrated that addictive use of social media was related to lower self-esteem. Malik and Khan (2015) found a significant relationship between Facebook addiction and the prediction of low self-esteem and narcissistic behaviour. However, Zhou and Leung (2012) found that self-esteem was not a significant predictor of addiction to social network sites (SNS) games, and Best, Taylor, and Manktelow (2015) indicated that using social media could enhance individuals' self-esteem through the accumulation of friends and followers. Additionally, Wilson, Fornasier, and White (2010) revealed that while self-esteem factors had some influence on social network service use and addictive tendencies, there were other unaccounted factors contributing to a large proportion of the unexplained variability in either the level of SNS use or the addictive tendency. These findings closely align with the results of this study.

Finally, the study on social media use in Hungarian adolescents had several strengths, including a large representative sample and the use of validated instruments. However, it also had certain limitations. Firstly, it focused solely on Hungarian adolescents, which called for cross-cultural studies to validate the findings in different cultural contexts. Additionally, relied on self-report data introduced potential biases (Braghieri, Levy and Makarin 2022), and caution should have been exercised when interpreting survey-based prevalence rates to avoid pathologising normal behaviours (van der Linden 2015). The controversial nature of social media addiction was acknowledged (Kuss and Griffiths 2011; van der Linden 2015). Moreover, the cross-sectional design of the study limited the ability to establish causal relationships between excessive social media use and mental health outcomes in adolescents. Longitudinal research is necessary to delve deeper into understanding these causal connections (Carbonell and Panova 2017). It was also important to consider that participants may have had different conceptions of social media use, including activities beyond social networking (Kuss and Griffiths 2011). To address these limitations, future studies should involve diverse cultures, employ longitudinal designs, and refine measurement tools to ensure accurate assessment of social media use in adolescents.

Chapter 5 Conclusion

The results of the present study indicated that the Bergen Social Media Addiction Scale (BSMAS) was a psychometrically valid tool for identifying risky social media use among adolescents. Consequently, it could be utilised in prevention and intervention programs in school settings, such as implementing content-control software, providing counselling services, or employing cognitive-behavioural therapy that targeted withdrawal symptoms. Furthermore, the study found that the BSMAS had a direct influence on depression (CES-D), but not on self-esteem (RSES). This suggested that prevention and intervention programs should prioritise addressing depressive symptoms when adolescents exhibited highly addictive social media behaviours.

In terms of future recommendations, it would be beneficial to replicate the study using similar large-scale nationally representative samples from other countries. Additionally, including adults in the study would help determine the prevalence of problematic social media usage across different age groups and enable comparisons. Furthermore, extending the study to incorporate anxiety symptoms would allow for investigation into whether the BSMAS also affects anxiety levels in adolescents.

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Appendices

Appendix A: Original paper and replicated data analysis available in GitHub: https://github.com/vim55/EFB_research_proj.git

Appendix B: Final data sample of 5,525 and its statistics.

Data	Range statistic	Additional information
Gender (number)	1 - male OR 2 - female	Number of Male = 2668 Number of Female = 2857
Age (number)	Age between 15 - 22	Most population are within aged 16 (2296) and 17 (2008)
Weekly internet use (number)	min 0.5, max 42 hours, mean 23.55 hours	This variable is calculated as following: (C37_weekday_sum * C38a_R) + (C37_weekend_sum * C38b_R)
Weekly social media use (number)	min 0.5. max 42 hours, mean 23.19 hours.	This variable is calculated as following: C39a_R*C40a_R if ~ ((C39a_R=0 & C40a_R ~= 0) | (C39a_R ~= 0 & C40a_R=0))
Self-esteem score (number)	min 1, max 4, mean 2.73	This average of all depression scale variable (RSES)
Level of depressive symptoms (number)	min 1, max 4, mean 1.93	This average of all depression scale variable (CESD)
FB1 (number)	min 1, max 5, mean 1.98	Part of BSMAS questionnaire - Salience
FB2 (number)	min 1, max 5, mean 1.55	Part of BSMAS questionnaire - Tolerance
FB3 (number)	min 1, max 5, mean 1.46	Part of BSMAS questionnaire - Mood mod
FB4 (number)	min 1, max 5, mean 1.63	Part of BSMAS questionnaire - Relapse
FB5 (number)	min 1, max 5, mean 1.41	Part of BSMAS questionnaire - Withdrawal symptoms
FB6 (number)	min 1, max 5, mean 1.82	Part of BSMAS questionnaire - Conflict

Note: The above statistics are calculated with final sample size of 5,525. Thus, there might be a slight difference in statistic as shown by the original paper.

Appendix C: Mapping between survey data and BSMAS items

Data variable	Mapping BSMAS items	Reasons
FB1	Salience (Question - Spent a lot of time thinking about SM or planned use of SM)	Salience refers to when the activity becomes the most important activity in the person's life and dominates their thinking. E.g., the person is not actually engaged in the behaviour they will be thinking about the next time they will be.
FB2	Tolerance (Question - Spent more time on SM than initially intended)	Tolerance refers to the process whereby increasing amounts of the activity are required to achieve the former effects.
FB3	Mood mod (Question - Used SM in order to forget about personal problems)	Mood modification refers to the subjective experience that people report because of engaging in the particular activity. e.g., to destressing feel of 'escape' or 'numbing'
FB4	Relapse (Question -Tried to cut down on the use of SM without success)	Relapse behaviour is in smokers who often give up for a period only to return to full-time smoking after a few cigarettes.
FB5	Withdrawal symptoms (Question - Become restless or troubled if you have been prohibited from using SM)	Withdrawal symptoms refer to the unpleasant feeling states and/or physical effects which occur when the activity is discontinued or suddenly reduced
FB6	Conflict (Question - Used SM so much that it has had a negative impact on your job/studies)	Conflict refers to conflicts between the addict and those around them (interpersonal conflict) or from within the individual themselves (intrapsychic conflict) e.g., personal relationships, working or educational lives, or other social and recreational activities.

Appendix D: Full sensitivity analysis with cut-off points ranging from 12 to 23.

Cut-off points	True positive	True negative	False positive	False negative	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)
Author's Result									
12	243	4304	1224	0	100	78	17	100	79
13	243	4635	895	0	100	84	21	100	84
14	243	4823	701	0	100	87	26	100	88
15	243	4986	539	0	100	90	31	100	91
16	240	5141	386	3	99	93	38	100	93
17	232	5249	278	9	96	95	45	100	95
18	219	5340	188	23	90	97	54	100	96
19	**199**	**5458**	**74**	**40**	**83**	**99**	**73**	**99**	**98**
20	177	5503	29	64	73	99	86	99	98
21	156	5517	17	85	65	100	90	98	98
22	126	5527	8	114	53	100	94	98	98
23	107	5530	4	133	45	100	96	98	98
Replicated Result									
12	448	4134	941	2	100	81	32	100	83
13	443	4439	636	7	98	87	41	100	88
14	438	4620	455	12	97	91	49	100	92
15	431	4763	312	19	96	94	58	100	94
16	411	4890	185	39	91	96	69	99	96
17	383	4972	103	67	85	98	79	99	97
18	**340**	**5022**	**53**	**110**	**76**	**99**	**87**	**98**	**97**
19	**236**	**5047**	**28**	**214**	**52**	**99**	**89**	**96**	**96**
20	191	5069	6	259	42	100	97	95	95
21	163	5073	2	287	36	100	99	95	95
22	129	5074	1	321	29	100	99	94	94
23	108	5075	0	342	24	100	100	94	94