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Social media and student academic performance: A cross-country analysis using PISA 2018

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Abstract

The pervasive use of social media is reshaping how the emerging generation communicates, learns, and thinks. As such, examining its impact on academic performance has grown increasingly important. The purpose of this study is to investigate the effects of social media usage on students' learning outcomes, using data from the Programme for International Student Assessment (PISA) 2018 database. In order to eliminate selection bias and assess the causal effect of using social media on learning, this research used propensity score matching (PSM) as an approach. By conducting analyses in each participating country, we were able to observe how the effects of social media use for school learning vary in different social, cultural, and political contexts. After obtaining the average treatment effects of each country, we find that the effects of social media use on learning varied significantly by country. In countries such as Mexico and Turkey, a positive relationship was observed between social media usage for academic purposes and student performance. Conversely, in countries such as the US and UK, a negative relationship was evident. Although the reasons behind these contrasting outcomes across countries remain outside the scope of this paper, the conclusions and practical implications are presented with caution, acknowledging the limitations of our research and indicating potential areas for further exploration.

Keywords:
PISA
Propensity score matching
Social media
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1. Introduction

A majority of internet users frequently engage with prominent social media platforms such as Facebook, Snapchat, and Instagram and this trend is even more pronounced among younger demographics (Anderson & Jiang, 2018; Auxier & Anderson, 2021). In addition, data from global reports underscore this trend, revealing that individuals, on average, dedicate over two hours daily to these social media platforms (Global Social Media Stats, 2022). These statistics come as no surprise to educators who are well-acquainted with the digital habits of contemporary teenagers and college students. However, the scope of social media usage has transcended mere social interaction and entertainment, especially among students. It has seamlessly integrated into their daily learning routines, influencing both academic and non-academic activities. This growing intersection of social media and education has piqued the interest of scholars, as evidenced by a surge in research on the topic (Gikas & Grant, 2013; Selwyn & Stirling, 2016). Consequently, the conversation surrounding the influence of social media in educational settings has become increasingly significant. This study, using large-scale international assessment data, aimed to investigate the impact of social media use on academic performance among students in various countries.

2. Literature Review

2.1. Social Media use and Academic Performance

The academic discourse concerning the influence of social media on academic performance has generated diverse findings in recent years. The literature reveals a dichotomy where some research demonstrates a negative correlation between social media usage and academic performance, while other studies suggest possible positive impacts.

Several researchers, such as Lau (2017) and Habes, Alghizzawi, Khalaf, Salloum, and Ghani (2018), found a negative correlation between social media usage and academic performance. Skiera, Hinz, and Spann (2017) proposed that such digital activities, particularly during class hours, can serve as distractions, hindering students' focus and note-taking capabilities.

Contrastingly, a strand of research indicates that social media could have a positive influence on academic performance. For instance, Talaue, AlSaad, AlRushaidan, AlHugail, and AlFahhad (2018) argued that social media communication among peers can foster socialization, help establish new friendships, and facilitate discussions on academic-related issues, consequently enhancing academic performance.

Interestingly, Tafesse (2022) offered a more nuanced perspective, suggesting a curvilinear U-shaped relationship between social media use and college students' academic performance. This suggests that both low and high levels of social media usage could negatively affect academic performance, while moderate usage might prove beneficial.

However, it's important to recognize the role of individual and contextual factors that could moderate the relationship between social media use and academic performance (Al-Azawei, 2019; Hitchcock & Young, 2016; Piki, 2020; Van Den Beemt, Thurlings, & Willems, 2020). The current literature calls for further exploration to understand the complex interplay between these factors and how they may influence the relationship. This underscores the multifaceted nature of social media's impact on academic performance and the need for continued investigation into this intriguing phenomenon.

2.2. Theoretical Perspectives on Social Media and Student Learning

2.2.1. Connectivism as a Learning Theory in Digital Age

In the realm of education and learning, multiple theories have emerged over the years, each with its distinct perspective. Traditional learning theories, such as behaviorism, cognitivism, and constructivism, have provided valuable insights into the process of learning. However, as technology, particularly digital technology, continues to evolve and permeate various aspects of our lives, there has been a growing need to develop learning theories that encapsulate the changing dynamics of learning in the digital age. These learning theories, however, mainly predate the advent of modern technology and the rise of the internet and social media. George Siemens, recognizing that these traditional learning theories could not fully account for the impact of technology on learning, introduced the theory of connectivism (Siemens, 2004, 2005). Stephen Downes further characterized connectivism as the process of constructing and traversing knowledge networks (Downes, 2007). Essentially, connectivism posits that learning occurs through interconnected networks, reflecting the reality of the digital age where information is often distributed across various platforms and sources (Duke, Harper, & Johnston, 2013).

Connectivism acknowledges and addresses the unique learning dynamics brought about by technological advancements. Traditional learning models are being challenged as new forms of knowledge acquisition and dissemination emerge. Today's learners often engage in lifelong learning, traversing multiple career paths and relying heavily on digital technologies for information access and knowledge construction (Siemens, 2004).

Moreover, the rise of digital devices and technologies such as smartphones, the internet, and social media apps has shifted the cognitive processes involved in learning. Rather than solely relying on individual cognitive capacities for memorization and recall, learners can now off-load some of these processes to digital technologies (Siemens, 2004).

Informal learning has also gained significance in today's learning landscape. As Siemens (2004) highlights, knowledge is no longer confined to formal educational settings. Internet technology and social media have created diverse channels for knowledge acquisition, allowing learners to engage with communities of practice and personal networks. In this context, knowing where to find the needed knowledge is as important as knowing the information itself.

2.2.2. Theory of Multitasking

The theory of media multitasking suggests that students who engage in simultaneous use of social media while studying are likely to experience a decrease in their ability to focus on a single task, leading to a reduction in their academic performance (Lau, 2017; Mohammed, Ibrahim, & Yunus, 2021). This phenomenon, commonly referred to as multitasking, has been found to have a negative effect on student's cognitive ability, academic performance, and overall self-efficacy. When students engage in social media use while studying, they are likely to experience a decrease in their ability to focus on a single task. This can lead to lower academic performance, as seen in studies that have found a negative correlation between social media use for non-academic purposes (such as video gaming) and academic performance as measured by cumulative grade point average (Lau, 2017).

Additionally, research has shown that social media usage and multitasking are associated with students' self-efficacy and academic performance (Mohammed et al., 2021). This theory highlights the importance of understanding the impact of social media use on students' academic performance, and the need for responsible and mindful usage of these technologies.

2.2.3. Theory of Information Overload

The Theory of Information Overload posits that the excessive use of mobile social networking sites can result in individuals feeling overwhelmed by the amount of information they are exposed to, leading to negative impacts on their well-being. Research has found that perceptions of information overload are a significant predictor of depressive symptoms and can negatively affect an individual's well-being over time (Matthes, Karsay, Schmuck, & Stevic, 2020). This theory is further supported by the Cognitive Overload Theory, which states that the human mind has a limited capacity for processing new knowledge and that excessive cognitive load or a flood of complicated information can exceed this capacity (De Jong, 2010; Isaksen & Oslo, 2014). Information overload can take on three forms: too much information, not enough time, and poor quality information (Agnew & Szykman, 2005).

The impact of social media use on students can be related to the theory of information overload. Mobile social networking sites (SNS) or social media are frequently considered a source of perceived information overload, leading to negative effects on well-being. This theory suggests that constant exposure to vast amounts of information through SNS can lead to cognitive overload, as students struggle to process the large volume of information they are exposed to.

2.3. Cross-Cultural Perspectives on Social Media Use in Education

The previous studies indicate that the impact of social media on education and academic performance can differ greatly depending on various cultural, social, and political factors. In countries like China, South Korea, and Taiwan, the use of social media in education is widely accepted and encouraged as a means to facilitate learning and collaboration (Athukorala, 2018; Tang, Omar, Bolong, & Mohd Zawawi, 2021). In these countries, there are specialized platforms and services that are specifically designed for educational purposes.

In countries like the United States and the United Kingdom, the use of social media in education is more controversial (Krutka et al., 2019; Taylor, King, & Nelson, 2012). While some educators and institutions embrace its potential to enhance student engagement and facilitate collaboration, others are concerned about its potential to distract students and undermine academic integrity.

In developing countries, access to technology and the Internet remains a major barrier to the widespread adoption of social media in education. However, some initiatives have been undertaken to bring technology and internet access to schools and communities, so that students and teachers can benefit from the educational potential of social media. In countries with strict censorship laws and limited internet freedom, the use of social media in education may be limited or banned altogether (Wu & Alaimo, 2018). In these countries, it is important for educators and policymakers to carefully consider the potential benefits and risks of social media use in the classroom and to balance academic freedom with the need for security and stability.

The intricate interplay between social media usage and academic achievements is shaped by diverse personal and situational determinants. While some research points towards a detrimental effect of social media on learning performance, others highlight the potential benefits of using social media. The dynamics of this relationship can be understood through lenses such as social comparison, multitasking, information overload, and the quest for social support. Delving deeper into this topic is crucial to discern the nuances of how social media impacts learning, considering the influence of both individual characteristics and environmental contexts. It is important for students to approach their use of social media in a responsible and mindful manner to ensure that it does not have a negative impact on their academic performance.

3. Methodology

The primary objective of this study was to delve into the relationship between students' usage of social media and their academic performance, as quantified by the 2018 round of Programme for International Student Assessment (hereafter referred to as "PISA 2018"). The study was designed around a central research question:

What is the impact of social media use on students' academic performance as measured by PISA 2018?

The importance of this research question arises from the pervasive nature of social media usage among students and the potential implications it could have on their academic performance. In addition to probing the overarching influence of social media usage on academic performance, the study also aimed to address a secondary research question:

How do the effects of social media usage on academic performance vary across diverse cultural and national backgrounds?

Exploring the secondary question will allow for uncovering potential cultural and national disparities in the relationship between social media usage and academic performance. Understanding these disparities could be instrumental in informing education policies and practices tailored to different cultural and national contexts.

As the PISA data used in this study was obtained from a non-experimental assessment, in order to answer these questions, propensity score analysis was used to establish a valid causal inference. Propensity score matching (PSM) is used to control for potential confounding factors and examine the causal effect of social media use on students' PISA scores.

3.1. Data

The present study uses data from the Program for International Student Assessment (PISA), a globally recognized evaluation conducted every three years, assessing the academic abilities of 15-year-old students. PISA assessed students' knowledge and skills in mathematics, reading, and science, providing a comprehensive measure of their educational achievement. In addition, PISA collects a wealth of information on students and schools through its student and school questionnaires. The information gathered covers various aspects of students' home and family backgrounds, as well as the school environment, across all participating countries. A total of 79 countries and economies participated in PISA 2018. One of the unique features of PISA 2018 is its inclusion of specific variables related to Information and Communication Technology (ICT) at the student level (OECD, 2019). These variables provide insights into how students use social media in this study.

While all countries and partners that participated in PISA 2018 provided assessment scores on mathematics, reading, and science achievement, only 31 OECD (Organization for Economic Co-operation and Development) countries and 19 partners provided survey data on students' use of information and communication technologies (ICT), including social media. Therefore, our analysis is based on data from these 50 countries and partners only. The administration of the ICT Familiarity Questionnaire varied among participating countries, and this determined the selection of countries to be included in the analysis. The countries and economies are listed below in Table 1 with the participant number of students.

Table 1. OECD's countries and partners participating in the ICT questionnaire.

OECD countries	Participants no.	OECD patterners	Participants no.
Australia	14273	Albania	6359
Austria	6802	Brazil	10690
Belgium	8475	Brunei Darussalam	6828
Chile	7621	Bulgaria	5294
Czech Republic	7019	Chinese Taipei	7243
Denmark	7657	Costa Rica	7221
Estonia	5316	Croatia	6609
Finland	5649	Dominican Republic	5674
France	6308	Georgia	5572
Greece	6403	Hong Kong (China)	6037
Hungary	5132	Kazakhstan	19507
Iceland	3296	Macao (China)	3775
Ireland	5577	Malta	3363
Israel	6623	Morocco	6814
Italy	11785	Russian Federation	7608
Japan	6109	Serbia	6609
Korea	6650	Singapore	6676
Latvia	5303	Thailand	8633
Lithuania	6885	Uruguay	5263
Luxembourg	5230		
Mexico	7299		
New Zealand	6173		
Poland	5625		
Slovak Republic	5965		
Slovenia	6401		

OECD countries	Participants no.	OECD patterners	Participants no.
Spain	35943		
Sweden	5504		
Switzerland	5822		
Turkey	6890		
United Kingdom	13818		
United States	4838		

3.2. Measurement

This study makes use of three distinct sets of variables see Table 2 in its analysis. The primary outcome variables are the scores of 15-year-old students in mathematics, reading, and science, as assessed by PISA 2018. These scores are utilized as a measure of academic performance and serve to assess the impact of social media use on students' academic outcomes.

The treatment variable in this study is the frequency of social media use for communication among 15-year-old students regarding schoolwork. This variable is measured through the IC010Q05NA item in the information and communication technologies (ICT) questionnaire of PISA 2018. The item specifically asks students about their use of social media platforms, such as Facebook and MySpace, for communication with other students about school-related matters.

In order to control for potential confounding factors, the study employs a group of ten covariates, which include demographic information and an ICT use index. These covariates are used in propensity score matching to balance the treatment and control groups and to ensure that the observed effect of social media use on academic performance is not biased by other variables.

By utilizing these three sets of variables, the study provides a comprehensive examination of the relationship between social media use and academic performance, while taking into account the potential impact of other relevant factors. The careful consideration and use of these variables are crucial in ensuring the validity and reliability of the study's findings. All the variables and their definitions are listed in the table below.

Table 2. Variable categories, names, and definitions.

Variable category	Variable name	Variable definition
Outcome variable	Science_w	Weighted science score
	Reading_w	Weighted reading score
	Maths_w	Weighted math score
Treatment variable	IC010Q05NA	How often use social networks such as Facebook and MySpace for communication with other students about sshool-related matters
Covariates	ST004D01T	Student (Standardized) gender
	MISCED	Mother's education
	FISCED	Father's education
	IMMIG	Index immigration status
	ESCS	Economic, social and cultural status
	PERCOOP	Perception of cooperation at school
	ICTHOME	ICT available at home
	ICTSCH	ICT available at school
	INTICT	Interest in ICT
	COMPICT	Perceived ICT competence

This study used propensity score matching as a statistical technique to estimate the causal effect of a treatment on an outcome by controlling for a range of confounding factors (Rosenbaum & Rubin, 1983). It involves estimating the probability that a subject will receive a particular treatment, based on their characteristics as measured by a set of covariates. Through weighting and matching participants based on their propensity scores, researchers can reduce selection bias and obtain more valid estimates of the treatment's causal effect. In this study, propensity score matching is used to control for potential confounders and examine the relationship between students' use of social media for communication about schoolwork and their scores on the mathematics, reading, and science assessments of PISA 2018.

3.3. Analysis

Based on the suggestions outlined in previous literature (Agasisti, Gil-Izquierdo, & Han, 2020; Hogrebe & Strietholt, 2016; Jiang & McComas, 2015), the causal analysis in this study consisted of the following major steps:

(1) Selection of the covariates

The first step in the causal analysis in this study was the selection of covariates. This involved identifying the relevant variables that could potentially affect the outcome of interest and serve as confounding factors. The outcome variables and the treatment variables were selected from the PISA 2018 questionnaire based on the research questions of this study. The covariate variables were selected based on the literature and the researchers' own experience.

(2) Estimation of the propensity scores

In this study, propensity score matching (PSM) was used to create comparable treatment and control groups of students based on their propensity scores. The matching method employed was nearest neighbor matching with a caliper, which involves finding the nearest untreated subject to each treated subject and forming a pair, as long as the difference in their propensity scores is within a specified range known as the caliper. The caliper is typically set at a small value to ensure that the treatment and control groups are well-matched on the covariates. In this study, the caliper was set at 2.5 to allow for a larger pool of matched subjects and increase the statistical power of the analysis. This method helps to control for potential confounders and reduce the influence of selection bias on the estimates of the treatment effect.

(3) Matching or weighting of treatment and control groups based on propensity scores

The next step in the causal analysis was to match or weigh the treatment and control groups based on their propensity scores. This step was achieved through propensity score matching (PSM) using the nearest neighbor matching method with a calliper of 2.5. The aim of this step was to create comparable treatment and control groups of students based on their propensity scores, which helps control for potential confounders and reduce the influence of selection bias on the estimates of the treatment effect.

(4) Estimation of the treatment effect on the outcome variable

The final step in the causal analysis was the estimation of the treatment effect on the outcome variable. This involved comparing the outcomes of the treated and untreated groups after controlling for potential confounding factors through the matching or weighting process. The outcome of this analysis provides insight into the causal effect of the treatment on the outcome of interest.

4. Results

This study employed a meticulous approach to data analysis by conducting separate propensity score analyses for each country or economy involved. This strategy allowed for a comprehensive evaluation of the data from each country and facilitated the identification of country-specific patterns and trends. In the results section, the analysis of U.S. data serves as a detailed example to illustrate the study's methodology. Utilizing the Propensity Score Matching (PSM) approach, the study divided participants into experimental and control groups to examine the impact of social media use for after-school learning on students' academic scores in math, reading, and science. This process was replicated for other participating countries, and the findings are consolidated in a table for cross-country comparison. This multidimensional analysis offers a comprehensive insight into the data, uncovering its nuances and complexities. By evaluating the results at both country-specific and global levels, the study provides a more profound understanding of the underlying patterns and trends. This approach not only highlights the significance of the impact but also enables a more coherent interpretation of the relationship between social media use and academic performance across different cultures and educational systems.

4.1. Results of the US

The regression analysis for the United States' data in Table 3, incorporates 11 independent variables. These variables include: IC010Q05NA (indicating how often students use social networks like Facebook and MySpace for communication with other students about school-related matters), ST004D01T (representing the standardized gender of the student), MISCED (indicating the educational level of the mother), FISCED (indicating the educational level of the father), IMMIG (denoting the immigration status index), ESCS (representing the Economic, Social, and Cultural Status), ICTHOME (measuring the availability of ICT at home), ICTSCH (measuring the availability of ICT at school), PERCOOP (indicating the student's perception of cooperation at school), INTICT (showing the student's interest in ICT), and COMPICT (representing the perceived competence in ICT). The model aims to predict the dependent variable: Science score. The F-statistic for the model is 81.38 and the p-value is less than 0.0000, which means that the overall model is significant at the 5% level. The R-squared value is 0.1841, which indicates that 18.41% of the variation in the outcome variable is explained by the independent variables in the model. However, although the results of the regression operation showed a correlation between social media use and students' academic performance, no causal relationship could be drawn. Therefore, after the regression analysis of the variables, this study continued with the PSM analysis.

Table 3. Regression outcome of the US data.

Source	SS	df	MS	Number of obs = 3, 980	
Model	6053325.24	11	550302.295	F (11, 3968) = 81.38	
Residual	26831109.6	3, 986	6761.872	Prob>F = 0.000	
Total	32884434.8	3, 979	8264.497	R-squared = 0.184 Adj R-squared = 0.181 Root MSE = 82.231	

Science_w	Coefficent	Std. err.	t	P>|t|	[95% conf. interval]	
IC010Q05NA	-13.999	2.830	-4.95	0.000	-19.548	-8.450
ST004D01T	5.645	2.662	2.12	0.034	0.425	10.865
MISCED	-6.670	1.382	-4.83	0.000	-9.380	-3.961
FISCED	0.575	1.238	0.46	0.642	-1.853	3.003
IMMIG	5.053	2.525	2.00	0.045	0.102	10.004
ESCS	46.017	2.290	20.09	0.000	41.527	50.506
ICTHOME	-6.556	0.764	-8.58	0.000	-8.055	-5.057
ICTSCH	-4.253	0.684	-6.21	0.000	-5.595	-2.911
PERCOOP	1.179	1.409	0.84	0.403	-1.583	3.941
INTICT	6.168	1.618	3.81	0.000	2.995	9.340
COMPICT	6.237	1.674	3.75	0.000	2.992	9.555
_cons	606.812	11.996	50.58	0.000	583.292	630.331

Table 4 shows the results of a propensity score matching (PSM) analysis. After running logistic regression with the nearest neighbor matching with caliper 2.5, the number of observations was assigned to "Treated" and "Untreated" based on each matching score. The "Common Support" column in Table 4 shows the number of observations in the overlapping region of the two groups, which is defined by the propensity score. This is the number of observations that can be compared between the two groups, as they have similar observed characteristics. In the example of the US, there are 2,568 observations in the "Untreated" group and 1,412 observations in the "Treated" group that are part of the common support.

Table 4. The outcome of PSM.

Psmatch2: Treatment assignment	Psmatch2: Common support on support	Total
Untreated	2. 568	2. 568
Treated	1. 412	1. 412
Total	3.980	3. 980

After matching the treated and untreated groups based on each individual's propensity score, the difference in the average treatment effects (ATT) between the groups can be seen. Table 5 presents the difference in the mean values of three variables: Science_w, Reading_w, and Maths_w, between the treated and untreated groups both before and after matching. The t-statistic provides information on the statistical significance of the difference in means between the groups. It can be seen that after matching, the difference between the means of the treated and untreated groups has increased and is statistically significant for all three variables, as indicated by the t-values.

Table 5. The outcome of average treatment effect on treated (ATT).

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Science_w	Unmatched	504.769	510.079	-5.310	3.011	-1.76
	ATT	504.769	520.107	-15.338	4.327	-3.54
Reading_w	Unmatched	511.482	513.831	-2.349	3.337	-0.70
	ATT	511.482	529.514	-19.032	4.727	-3.81
Maths_w	Unmatched	481.962	482.916	-0.954	2.762	-0.35
	ATT	481.962	493.468	-11.506	3.973	-2.90

4.2. Results of All the Countries and Partners

As with the US data, we also analyzed data from other 49 countries and economies participating PISA2018 and providing data on information and communication technologies ICT survey data see Table 6. Table 6 shows the corresponding t-values of the treatment effects for the three subjects after propensity score matching for each country and economy.

Table 6. The T-statistics of all 50 counties and economies.

Countries and economies	Reading_t	Maths_t	Science_t	Countries and economies	Reading_t	Maths_t	Science_t
Australia	-2.68	-0.54	-1.82	Spain	-6.08	-6.61	-5.18
Austria	0.87	0.2	0.8	Sweden	-2.95	-3.41	-2.72
Belgium	3.23	2.25	1.81	Switzerland	-1.24	-1.74	-1.75
Chile	-0.3	-0.61	-2.06	Turkey	1.9	0.65	1.48
Czech Republic	2.35	1.9	1.74	United Kingdom	-3.69	-2.55	-3.6
Denmark	-3.16	-3.4	-4.53	United States	-3.81	-2.9	-3.54
Estonia	3.25	1.08	2.64	Albania	2.83	0.72	2.42
Finland	-3.42	-2.21	-2.67	Brazil	2.75	0.94	1.32
France	-1.11	0.25	-1	Brunei Darussalam	3.08	3.95	3.31
Greece	-1.45	-1.9	-2.52	Bulgaria	2.36	2.38	1.78
Hungary	3.12	2.41	2.16	Chinese Taipei	-1.59	-1.82	-0.81
Iceland	-0.98	-1.25	-1.73	Costa Rica	-6.14	-5.53	-6.41
Ireland	-2.39	-1.69	-3.16	Croatia	4.54	3	4
Israel	-3.24	-3.22	-3.49	Dominican Republic	1.04	1.74	1
Italy	-2.81	-4.52	-2.43	Georgia	-0.17	-1.22	-0.17
Japan	-4.82	-2.53	-3.79	Hong Kong	-1.94	-2.14	0.03
Korea	-0.45	-2.02	-2.75	Kazakhstan	16.23	11.24	14.54
Latvia	0.06	-0.47	-2.1	Macao	0.93	1.67	1.43
Lithuania	1.13	1.36	1.1	Malta	0.12	-0.73	-1.18
Luxembourg	2.04	2.14	0.93	Morocco	0.31	0.37	0.24
Mexico	2.17	1.19	1.73	Russian	1.99	1.04	2.32
New Zealand	-4.38	-3.44	-5.11	Serbia	3.55	2.32	2.5
Poland	2.54	2.06	1.55	Singapore	1.93	2.85	3.01
Slovak Republic	4.08	2.66	3.97	Thailand	1.4	1.12	-0.29
Slovenia	5.28	4.33	4.3	Uruguay	-1.8	-1.68	-2.06

Results from 50 participating countries reveal that 38 of them demonstrate a significant correlation between assessment score in at least one of the subjects - math, reading, or science - and social media use for learning. Among these, 19 countries, including Belgium, the Czech Republic, Estonia, Hungary, Luxembourg, Mexico, Poland, the Slovak Republic, Slovenia, Turkey, Albania, Brazil, Brunei Darussalam, Bulgaria, Croatia, Kazakhstan, the Russian Federation, Serbia, and Singapore, exhibit a significant positive causal relationship, where social media use is linked with better academic performance. Conversely, the remaining 19 countries, such as Australia, Chile, Denmark, Finland, Greece, Ireland, Israel, Italy, Japan, Korea, Latvia, New Zealand, Spain, Sweden, the United Kingdom, the United States, Costa Rica, Hong Kong, and Uruguay, indicate a significant negative causality, implying that social media use may be detrimental to academic success.

Additionally, 12 countries, including Austria, France, Iceland, Lithuania, Switzerland, Chinese Taipei, Dominican Republic, Georgia, Macao, Malta, Morocco, Thailand, show no significant results at any reading, science, or math score. This means that in those countries, students' use of social media in after-school learning does not significantly affect their academic performance.

It is important to note that these results were found after conducting separate PSM analyses for each of the 50 OECD countries and partners participating PISA 2018, highlighting the variability in the relationship between social media use and academic performance across different countries and education systems. These results provide insight into the potential impact of social media use on students' academic performance and can inform future research and policy efforts in the field of education technology and media use in schools. It is also worth exploring the reasons behind the positive and negative causal relationships observed in different countries and economies to further understand the role of social media in student learning.

5. Discussion and Conclusions

Our study aimed to investigate the impact of social media use on students' academic performance. We conducted an analysis of the effect of social media use on academic performance using data from PISA 2018. By employing Propensity Score Matching, we explored the potential causal relationship between these variables, aiming to understand how social media might influence students' educational outcomes. In our results, the impact of social media on students' academic performance varied greatly among the 50 participating countries. The results of 38 out of 50 countries and collaborators showed a significant positive or negative impact, which means that for students in some countries, the use of social media in their studies had a positive impact on performance, while for students in other countries, it had a negative impact. In addition, 12 out of 50 participating countries and partners had non-significant results.

Our findings are consistent with other mixed result of previous studies. When discussing the impact of social media on student learning, contrasting results are obtained across countries, regions, and education systems (Appel, Marker, & Gnambs, 2020; Evans, 2014; Gikas & Grant, 2013; Odell, Galovan, & Cutumisu, 2020). This highlights the variability in the relationship between social media use and academic performance across different countries and education systems. Despite these findings, it is important to continue exploring the reasons behind the positive and negative relationships observed in different countries. Since we analyzed each of the 50 countries and economies, further research can be conducted to explore whether different country characteristics significantly affect the impact of social media on students in that country.

This study is limited to the scope, within-country variation, and lack of explanation of causes. First, the study analyzed data from 50 countries and economies, but this sample is not representative of the entire world. The results obtained from the OECD's PISA data may not be applicable to countries outside of the organization, particularly African countries, which are not represented in the data. Second, it is crucial to emphasize that the disparities within a single country can sometimes surpass those observed between countries, although the study highlighted variations in the influence of social media on learning across different countries. This means that the results obtained in this study may not be generalizable to specific countries. Third, while the study found a significant relationship between social media use and academic performance, it failed to examine the reasons behind these differences. Further research may, based on each country's social and cultural context, explore the reasons why the impact of social media use on learning varies across countries.

References

Agasisti, T., Gil-Izquierdo, M., & Han, S. W. (2020). ICT use at home for school-related tasks: What is the effect on a student's achievement? Empirical evidence from OECD PISA data. *Education Economics, 28*(6), 601-620. https://doi.org/10.1080/09645292.2020.1822787

Agnew, J. R., & Szykman, L. R. (2005). Asset allocation and information overload: The influence of information display, asset choice, and investor experience. *The Journal of Behavioral Finance, 6*(2), 57-70. https://doi.org/10.1207/s15427579jpfm0602_2

Al-Azawei, A. (2019). What drives successful social media in education and e-learning? A comparative study on facebook and moodle. *Journal of Information Technology Education: Research, 18*, 253-274. https://doi.org/10.28945/4360

Anderson, M., & Jiang, J. (2018). Teens, social media & technology 2018. *Pew Research Center, 31*(2018), 1673-1689.

Appel, M., Marker, C., & Gnambs, T. (2020). Are social media ruining our lives? A review of meta-analytic evidence. *Review of General Psychology, 24*(1), 60-74. https://doi.org/10.1177/1089268019880891

Athukorala, A. (2018). Factors affecting use of social media by university students: A study at Wuhan University of China. *Journal of the University Librarians Association of Sri Lanka, 21*(2), 44-72. https://doi.org/10.4038/jula.v21i2.7917

Auxier, B., & Anderson, M. (2021). *Social media use in 2021. Pew research center: Internet, Science & Tech.* Retrieved from https://www.pewresearch.org

De Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science, 38*(2), 105-134. https://doi.org/10.1007/s11251-009-9110-0

Downes, S. (2007). *What connectivism is.* Retrieved from https://halfanhour.blogspot.com/2007/02/what-connectivism-is.html

Duke, B., Harper, G., & Johnston, M. (2013). Connectivism as a digital age learning theory. *The International HETL Review, 2013*(Special Issue), 4-13.

Evans, C. (2014). T witter for teaching: Can social media be used to enhance the process of learning? *british Journal of Educational Technology, 45*(5), 902-915. https://doi.org/10.1111/bjet.12099

Gikas, J., & Grant, M. M. (2013). Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media. *Internet and Higher Education, 19*(1), 18-26. https://doi.org/10.1016/j.iheduc.2013.06.002

Global Social Media Stats. (2022). *Data reportal.* Retrieved from https://datareportal.com/social-media-users

Habes, M., Alghizzawi, M., Khalaf, R., Salloum, S. A., & Ghani, M. A. (2018). The relationship between social media and academic performance: Facebook perspective. *International Journal of Information Technology and Language Studies, 2*(1), 12-18.

Hitchcock, L. I., & Young, J. A. (2016). Tweet, tweet!: Using live Twitter chats in social work education. *Social Work Education, 35*(4), 457-468. https://doi.org/10.1080/02615479.2015.1136273

Hogrebe, N., & Strietholt, R. (2016). Does non-participation in preschool affect children's reading achievement? International evidence from propensity score analyses. *Large-Scale Assessments in Education, 1*(4), 1-22. https://doi.org/10.1186/s40536-016-0017-3

Isaksen, G., & Oslo, A. (2014). Hey, your e-learning courses are giving me a cognitive overload. *IITSEC Proceedings 2014, Paper nr. 14008*, 10.

Jiang, F., & McComas, W. F. (2015). The effects of inquiry teaching on student science achievement and attitudes: Evidence from propensity score analysis of pisa data. *International Journal of Science Education, 37*(3), 554–576. https://doi.org/10.1080/09500693.2014.1000426

Krutka, D. G., Manca, S., Galvin, S. M., Greenhow, C., Koehler, M. J., & Askari, E. (2019). Teaching "against" social media: Confronting problems of profit in the curriculum. *Teachers College Record, 121*(14), 1-42. https://doi.org/10.1177/016146811912101410

Lau, W. W. (2017). Effects of social media usage and social media multitasking on the academic performance of university students. *Computers in Human Behavior, 68*, 286-291. https://doi.org/10.1016/j.chb.2016.11.043

Matthes, J., Karsay, K., Schmuck, D., & Stevic, A. (2020). "Too much to handle": Impact of mobile social networking sites on information overload, depressive symptoms, and well-being. *Computers in Human Behavior, 105*, 106217. https://doi.org/10.1016/j.chb.2019.106217

Mohammed, M. T. S., Ibrahim, F., & Yunus, N. (2021). Exploring the relationship of social media usage and multitasking of social media on self-efficacy and academic performance. *Jurnal Komunikasi: Malaysian Journal of Communication, 37*(1), 227-243. https://doi.org/10.17576/jkmjc-2021-3701-13

Odell, B., Galovan, A. M., & Cutumisu, M. (2020). The relation between ICT and science in PISA 2015 for bulgarian and finnish students. *EURASIA Journal of Mathematics, Science and Technology Education, 16*(6), 1-15. https://doi.org/10.29333/ejmste/7805

OECD. (2019). PISA 2018 results what students know and can do (PISA). *Organisation for Economic Co-operation and Development, 1*, 1-354. https://doi.org/10.1787/5F07C754-EN

Piki, A. (2020). *An exploration of student experiences with social media and mobile technologies during emergency transition to remote education*. Paper presented at the World Conference on Mobile and Contextual Learning.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41-55.

Selwyn, N., & Stirling, E. (2016). Social media and education… now the dust has settled. *Learning, Media and Technology, 41*(1), 1-5. https://doi.org/10.4324/9781315121697-1

Siemens, G. (2004). Elearnspace connectivism: A learning theory for the digital age. *Elearnspace. org*, 14-16.

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning, 2*(1), 3-10.

Skiera, B., Hinz, O., & Spann, M. (2017). Social media and academic performance: Does the intensity of facebook activity relate to good grades? . *Schmalenbach Business Review 2015, 67*(1), 54–72. https://doi.org/10.1007/BF03396923

Tafesse, W. (2022). Social networking sites use and college students' academic performance: Testing for an inverted U-shaped relationship using automated mobile app usage data. *International Journal of Educational Technology in Higher Education, 19*(1), 1-17. https://doi.org/10.1186/s41239-022-00322-0

Talaue, G. M., AlSaad, A., AlRushaidan, N., AlHugail, A., & AlFahhad, S. (2018). The impact of social media on academic performance of selected college students. *International Journal of Advanced Information Technology, 8*(4/5), 27–35. https://doi.org/10.5121/ijait.2018.8503

Tang, L., Omar, S. Z., Bolong, J., & Mohd Zawawi, J. W. (2021). Social media use among young people in China: A systematic literature review. *SAGE Open, 11*(2), 1-17. https://doi.org/10.1177/21582440211016421

Taylor, R., King, D. F., & Nelson, D. G. (2012). Student learning through social media. *Journal of Sociological Research, 3*(2), 29–35. https://doi.org/10.5296/jsr.v3i2.2136

Van Den Beemt, A., Thurlings, M., & Willems, M. (2020). Towards an understanding of social media use in the classroom: A literature review. *Technology, Pedagogy and Education, 29*(1), 35–55. https://doi.org/10.1080/1475939X.2019.1695657

Wu, J. C., & Alaimo, K. S. (2018). Social media in mainland China: Weak democracy, emergent civil society. Oxford research encyclopedia of communication. In (pp. 1–27). New York: Oxford University Press.