DOI: https://doi.org/10.38035/ijphs.v1i4
https://creativecommons.org/licenses/by/4.0/

Demographic Influences on Screen Time: Impacts on Academic Performance and Mental Health

Diyanshi Patel[1], Pooja Vyas[2], Dhara Patel[3], Aryan Shah[4], Rahul Chauhan[5], Andino Maseleno[6], R. Rizal Isnanto[7]
[1]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India, diyanshipatel171003@gmail.com
[2]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[3]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[4]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[5]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[6]Department of Information Systems, Institut Bakti Nusantara, Lampung, Indonesia, andino.maseleno@ibnus.ac.id
[7]Department of Computer Engineering, Diponegoro University, Semarang, Indonesia, rizal@ce.undip.ac.id

Corresponding author: andino.maseleno@ibnus.ac.id[6]

Abstract: This study examines the relationship between demographic factors—age, gender, and education level—and various aspects of screen time usage, including average screen time, academic performance, and associated health impacts such as anxiety and social life interactions. Using ANOVA, we found significant differences in average screen time based on age and education level, with younger and more educated individuals tending to engage more with digital devices for studying. Notably, academic performance was influenced by education level, while anxiety and social life were significantly affected by both education and age. These findings underscore the importance of considering demographic factors in understanding screen time behaviors. Future research should explore longitudinal effects and potential interventions to mitigate negative outcomes.

Keywords: Screen time, demographics, academic performance, mental health

INTRODUCTION

In the realm of medical education, David et al. (2024) evaluate the effectiveness of video tools in enhancing anatomy knowledge among medical postgraduates, illustrating how digital resources can address gaps in traditional learning methods. This study underscores the growing role of multimedia in educational settings, particularly in fields that demand detailed and complex understanding. Similarly, Dreisiebner et al. (2021) address the enhancement of information literacy through a multilingual Massive Open Online Course (MOOC), emphasizing the importance of cultural considerations in the design and delivery of educational

content. This approach highlights the need for inclusivity and accessibility in global educational initiatives.

The challenges of online education are further examined by Jutz et al. (2024), who explore the sustainability dilemmas faced by students engaged in remote learning. Their research underscores the need to balance academic flexibility with environmental concerns, reflecting broader societal shifts towards sustainable practices. In the field of cyber security, Meland et al. (2019) provide an experimental evaluation of bow-tie analysis, offering insights into advanced methodologies for risk management and security assessment. This study contributes to the ongoing discourse on enhancing security measures in an increasingly digital world.

In humanitarian contexts, Moreno Rocha et al. (2024) present the Mobile Ultrasound Vascular Assessment (MUVA) as a vital tool for remote and conflict-affected areas, demonstrating how technological innovations can improve healthcare delivery in challenging environments. Mostafa et al. (2024) discuss the impact of ASPECTSS-based design interventions on autism school environments, offering valuable insights into how architectural design can cater to the needs of individuals with autism. Lastly, Srivastava et al. (2024) analyze knowledge management during the transition to emergency remote teaching, providing an interpretative phenomenological perspective on the experiences of faculty members navigating this shift.

In today's rapidly advancing digital age, the need for awareness and intervention in technology-related health issues has become more pressing than ever (Sulaksono et al., 2023). As digital tools increasingly permeate educational and professional environments, their impacts on physical and mental well-being demand closer scrutiny. For instance, David et al. (2024) highlight the effectiveness of video tools in medical education, showing how multimedia can enhance learning in complex subjects like anatomy. However, these tools also raise concerns about screen time, posture, and cognitive overload. Similarly, Dreisiebner et al. (2021) stress the importance of culturally inclusive design in digital learning platforms, such as MOOCs, to ensure equitable access to education.The sustainability challenges of remote learning, as explored by Jutz et al. (2024), further underscore the environmental and health-related consequences of extensive technology use. In specialized fields like cyber security and healthcare, technological innovations, such as bow-tie analysis (Meland et al., 2019) and MUVA (Moreno Rocha et al., 2024), offer promising solutions but also present new health risks, including ergonomic strain and psychological stress.

METHOD

The study aims to assess the average screen time among students in Ahmedabad and evaluate its impact on academic performance and mental health. The primary objectives are to determine the relationship between screen time and both academic outcomes and mental health indicators such as anxiety and stress. To achieve this, two key research questions are posed: What is the average daily screen time of students in Ahmedabad, and how does it vary by age and education level? In addition, does increased screen time correlate with higher levels of anxiety and stress?

Objectives:

- To assess the average screen time among students in Ahmedabad and its impact on their academic performance and well-being.
- To evaluate the relationship between excessive screen time and mental health issues such as anxiety and stress among students.

Research Questions:

1. What is the average daily screen time of students in Ahmedabad, and how does it vary based on age and educational level?

2. Does increased screen time correlate with mental health issues such as anxiety and stress among students?

Hypotheses:
H1: There is a significant relationship between increased screen time and reduced academic performance among students in Ahmedabad.
H2: There is a significant correlation between increased screen time and higher levels of anxiety and stress among students

The study hypothesizes that there is a significant relationship between increased screen time and reduced academic performance, as well as a significant correlation between screen time and heightened anxiety and stress. A quantitative research approach is employed, utilizing both descriptive and correlational research designs. The sample consists of 100 students from Ahmedabad, selected using stratified random sampling to ensure representation across various age groups, educational levels, and socio-economic backgrounds. The participants, aged 15-25, must be currently enrolled in schools or colleges and report using digital devices for more than two hours per day.

Data will be collected through an online survey, where participants will answer a structured questionnaire. The survey will gather demographic information, average daily screen time, self-reported academic performance, and mental health status. Validated scales such as the Generalized Anxiety Disorder (GAD-7) for anxiety and the Perceived Stress Scale (PSS) for stress will be included to assess mental health outcomes.

For data analysis, SPSS (Statistical Package for the Social Sciences) will be used. Descriptive statistics will calculate the mean, median, and standard deviation for screen time, academic performance, and mental health scores. Pearson correlation will assess the relationship between screen time and both academic performance and mental health, while multiple regression analysis will be conducted to control for variables such as age and gender, exploring the direct impact of screen time on both academic and mental health outcomes. This methodological approach allows for a comprehensive understanding of the effects of screen time on students' academic success and psychological well-being.

RESULT AND DISCUSSION

The demographic data from the study provides a comprehensive overview of the participants, shedding light on their age, gender, education level, and family income. Among the 124 students surveyed, the age distribution indicates a predominance of participants aged 19-21, comprising 45.2% of the sample, followed by those aged 15-18 at 26.6%, and 22-25 at 28.2%. This distribution suggests that the study primarily captures insights from early university students, which may be particularly relevant given the context of academic performance and mental health.

Table-1: Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	15-18	33	26.6	26.6	26.6
	19-21	56	45.2	45.2	71.8
	22-25	35	28.2	28.2	100.0
	Total	124	100.0	100.0	

In terms of gender, the sample is fairly balanced, with 47.6% identifying as male, 46.8% as female, and 5.6% identifying as other. This representation allows for a more nuanced analysis of how screen time and its effects may vary across different genders.

Table-2: Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	59	47.6	47.6	47.6
	Female	58	46.8	46.8	94.4
	Other	7	5.6	5.6	100.0
	Total	124	100.0	100.0	

Regarding education level, a significant majority (62.1%) are undergraduates, while 25.0% are postgraduates and 12.9% are in high school. This focus on higher education students could reflect the increasing screen time associated with university coursework and social media use, making the findings particularly pertinent for understanding academic performance.

Table-3: Education level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school	16	12.9	12.9	12.9
	Undergraduate	77	62.1	62.1	75.0
	Post graduate	31	25.0	25.0	100.0
	Total	124	100.0	100.0	

Lastly, family income data reveals a skew toward higher income levels, with 63.7% of participants earning above INR 100,000 per month. This demographic factor may influence access to technology and digital devices, potentially impacting screen time and its associated effects on mental health and academic outcomes. Overall, the demographic data provides essential context for interpreting the study's findings, highlighting the diverse backgrounds of students and the potential implications for their screen time habits.

Table-4 : Monthly Family Income (in INR)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 25,000	18	14.5	14.5	14.5
	25,000-50,000	15	12.1	12.1	26.6
	50,000-1,00,000	12	9.7	9.7	36.3
	Above 1,00,000	79	63.7	63.7	100.0
	Total	124	100.0	100.0	

The ANOVA table presents the results of a study examining the relationship between age and various factors related to screen time, including average screen time, primary purpose of screen use, and its impact on health and social life. The analysis includes between group and within-group sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values).

Table 5: ANOVA between Age and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	10.845	2	5.422	4.929	.009
	Within Groups	133.115	121	1.100		
	Total	143.960	123			
Primary purpose	Between Groups	9.490	2	4.745	3.008	.053
	Within Groups	190.857	121	1.577		
	Total	200.347	123			
Studying device	Between Groups	2.461	2	1.231	7.980	<.001
	Within Groups	18.660	121	.154		
	Total	21.121	123			
Breaks taken	Between Groups	1.199	2	.600	.514	.599
	Within Groups	141.019	121	1.165		
	Total	142.218	123			
Academic performance	Between Groups	3.807	2	1.904	2.018	.137
	Within Groups	114.161	121	.943		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.268	2	2.134	2.218	.113
	Within Groups	116.409	121	.962		
	Total	120.677	123			
Stress levels	Between Groups	3.596	2	1.798	2.101	.127
	Within Groups	103.525	121	.856		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	7.515	2	3.757	3.465	.034
	Within Groups	131.219	121	1.084		
	Total	138.734	123			
Social life impact	Between Groups	2.455	2	1.228	2.169	.119
	Within Groups	68.472	121	.566		
	Total	70.927	123			
Sleep patterns	Between Groups	2.394	2	1.197	2.041	.134
	Within Groups	70.961	121	.586		
	Total	73.355	123			

For average screen time, the between-group F-value is 4.929, with a p-value of 0.009, indicating a statistically significant difference across age groups. This suggests that age significantly influences how much time individuals spend on screens. In contrast, the primary purpose of screen use shows a p-value of 0.053, which is marginally significant and suggests some variation in screen use purposes by age but does not meet conventional significance levels. Notably, the use of a studying device is highly significant ($p < 0.001$), indicating that age has a strong influence on whether individuals use digital devices for studying. This result suggests that older individuals may be less inclined to use digital devices for educational purposes compared to younger counterparts. Conversely, factors such as breaks taken ($p = 0.599$), academic performance ($p = 0.137$), headaches/eye strain ($p = 0.113$), and stress levels ($p = 0.127$) did not show significant differences across age groups, indicating that these aspects might be more consistent regardless of age.

The findings related to anxiety/restlessness (p = 0.034) suggest a significant relationship with age, indicating that different age groups may experience varying levels of anxiety due to excessive screen time. However, the impacts on social life and sleep patterns were not statistically significant, highlighting that while age influences certain aspects of screen use, other factors may need to be considered to understand these effects fully. Overall, the results indicate that age plays a crucial role in shaping screen time behaviors and their associated consequences.

Table 6: ANOVA between Gender and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	.520	2	.260	.219	.804
	Within Groups	143.440	121	1.185		
	Total	143.960	123			
Primary purpose	Between Groups	2.532	2	1.266	.774	.463
	Within Groups	197.815	121	1.635		
	Total	200.347	123			
Studying device	Between Groups	1.953	2	.977	6.166	.003
	Within Groups	19.168	121	.158		
	Total	21.121	123			
Breaks taken	Between Groups	1.611	2	.805	.693	.502
	Within Groups	140.607	121	1.162		
	Total	142.218	123			
Academic performance	Between Groups	8.148	2	4.074	4.489	.013
	Within Groups	109.820	121	.908		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.036	2	2.018	2.093	.128
	Within Groups	116.642	121	.964		
	Total	120.677	123			
Stress levels	Between Groups	3.621	2	1.810	2.116	.125
	Within Groups	103.500	121	.855		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	.679	2	.339	.297	.743
	Within Groups	138.055	121	1.141		
	Total	138.734	123			
Social life impact	Between Groups	2.762	2	1.381	2.452	.090
	Within Groups	68.165	121	.563		
	Total	70.927	123			
Sleep patterns	Between Groups	.807	2	.404	.673	.512
	Within Groups	72.547	121	.600		
	Total	73.355	123			

The ANOVA table examines the effects of gender on various factors related to screen time usage and its associated impacts. The analysis includes the sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values) for each factor. For average

screen time, the results indicate no significant differences between genders, with an F-value of 0.219 and a p-value of 0.804, suggesting that screen time does not vary meaningfully between male and female participants. Similarly, the primary purpose of screen use also shows no significant differences (p = 0.463), indicating that both genders use screens for similar purposes. In contrast, the use of studying devices reveals a statistically significant difference, with an F-value of 6.166 and a p-value of 0.003. This suggests that gender plays a crucial role in the likelihood of using digital devices for educational purposes, potentially indicating that one gender may be more inclined to utilize these devices for studying.

Academic performance also demonstrates a significant difference (p = 0.013), suggesting that gender may influence academic outcomes. This finding points to the possibility of differing study habits or engagement levels between genders. However, factors such as breaks taken (p = 0.502), headaches/eye strain (p = 0.128), stress levels (p = 0.125), anxiety/restlessness (p = 0.743), social life impact (p = 0.090), and sleep patterns (p = 0.512) did not show significant differences between genders, indicating relative consistency in these experiences regardless of gender. Overall, while gender appears to influence the use of studying devices and academic performance, the lack of significant differences in other factors suggests that the impact of gender on screen time-related behaviors and their consequences may be nuanced and context-dependent. Further research could provide deeper insights into these dynamics.

Table-6 ANOVA between Education Level and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	7.805	2	3.902	3.468	.034
	Within Groups	136.155	121	1.125		
	Total	143.960	123			
Primary purpose	Between Groups	8.045	2	4.023	2.531	.084
	Within Groups	192.301	121	1.589		
	Total	200.347	123			
Studying device	Between Groups	1.871	2	.936	5.881	.004
	Within Groups	19.250	121	.159		
	Total	21.121	123			
Breaks taken	Between Groups	1.451	2	.726	.624	.538
	Within Groups	140.766	121	1.163		
	Total	142.218	123			
Academic performance	Between Groups	7.852	2	3.926	4.314	.015
	Within Groups	110.116	121	.910		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.226	2	2.113	2.196	.116
	Within Groups	116.451	121	.962		
	Total	120.677	123			
Stress levels	Between Groups	2.309	2	1.155	1.333	.268
	Within Groups	104.812	121	.866		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	7.894	2	3.947	3.650	.029
	Within Groups	130.839	121	1.081		
	Total	138.734	123			

Social life impact	Between Groups	7.664	2	3.832	7.330	<.001
	Within Groups	63.263	121	.523		
	Total	70.927	123			
Sleep patterns:	Between Groups	2.522	2	1.261	2.155	.120
	Within Groups	70.832	121	.585		
	Total	73.355	123			

The ANOVA table investigates the relationship between education level and various factors related to screen time usage and its effects. This analysis includes the sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values) for each factor assessed. The results indicate a statistically significant difference in average screen time based on education level, with an F-value of 3.468 and a p-value of 0.034. This suggests that individuals with different education levels spend varying amounts of time on screens, potentially reflecting differing lifestyles or responsibilities associated with education.

The primary purpose of screen use also shows a trend toward significance ($p = 0.084$), indicating that the reasons for using screens may vary somewhat with educational attainment, although this does not reach conventional significance levels. However, the use of studying devices is highly significant ($p = 0.004$), suggesting that education level has a strong influence on the likelihood of utilizing digital devices for academic purposes, likely indicating that those with higher education levels may be more adept at integrating technology into their studies. Additionally, academic performance demonstrates a significant relationship with education level ($p = 0.015$), indicating that education may play a crucial role in determining academic outcomes. Anxiety and restlessness due to screen use also show significance ($p = 0.029$), suggesting that different education levels might experience varying levels of stress related to screen time.

The impact on social life is highly significant ($p < 0.001$), indicating that education level significantly affects how screen time influences social interactions. In contrast, other factors such as breaks taken ($p = 0.538$), headaches/eye strain ($p = 0.116$), stress levels ($p = 0.268$), and sleep patterns ($p = 0.120$) did not reveal significant differences across education levels.

Overall, the findings suggest that education level significantly influences several aspects of screen time behavior and its consequences, highlighting the importance of considering educational context when examining digital device usage.

CONCLUSION

In conclusion, this study highlights the significant relationships between age, gender, and education level with various factors related to screen time usage and its associated impacts. The findings suggest that demographics play a crucial role in shaping screen time behaviors, academic performance, and health outcomes such as anxiety and social life interactions. As technology continues to evolve, understanding these dynamics is essential for promoting healthy screen habits across different population segments.

Future research could explore longitudinal effects of screen time on mental health and academic performance, considering a more diverse demographic and geographical range. Additionally, investigating interventions aimed at reducing negative consequences of excessive screen use could yield valuable insights for educators, policymakers, and mental health professionals. Globally, as digital devices become increasingly integrated into daily life, understanding the implications of screen time on various populations is vital. This research can inform public health initiatives aimed at mitigating screen-related issues, fostering digital

literacy, and promoting balanced usage. Ultimately, addressing the global challenges posed by excessive screen time can contribute to healthier, more connected communities worldwide.

Acknowledgement

This research project is supported by **World Class University Program, Indonesia Endowment Fund for Education**, Diponegoro University, Indonesia. We gratefully appreciated this support.

REFERENCES

Agasisti, T., Falzetti, P., & Soncin, M. (2020). School principals' managerial behaviours and students' achievement. *International Journal of Educational Management*, *34*(5), 937–951. https://doi.org/10.1108/IJEM-11-2018-0350

Al-Ali, S., & Ahmed, A. (2015). E-textbooks in ESL classrooms: are learners on board? *Learning and Teaching in Higher Education: Gulf Perspectives*, *12*(2), 3–22. https://doi.org/10.18538/lthe.v12.n2.222

Ali, N. A., Feroz, A., Akber, N., & Khoja, A. (2024). Students' psychological state and its associated factors during an outbreak of COVID-19 in Pakistan: a web-based survey. *Arab Gulf Journal of Scientific Research*, *42*(2), 388–405. https://doi.org/10.1108/AGJSR-12-2022-0309

AlZahrani, W. I., & Oommen, A. (2023). Role of vitamin D in the academic performance of health sciences students in Saudi Arabia. *Arab Gulf Journal of Scientific Research*, *41*(1), 40–47. https://doi.org/10.1108/AGJSR-04-2022-0028

Ayandele, O., Popoola, O. A., & Oladiji, T. O. (2020). Addictive use of smartphone, depression and anxiety among female undergraduates in Nigeria: a cross-sectional study. *Journal of Health Research*, *34*(5), 443–453. https://doi.org/10.1108/JHR-10-2019-0225

Baj-Rogowska, A. (2023). Antecedents and outcomes of social media fatigue. *Information Technology & People*, *36*(8), 226–254. https://doi.org/10.1108/ITP-03-2022-0207

Boonroungrut, C., & Huang, F. (2021). Reforming theory of planned behavior to measure money management intention: a validation study among student debtors. *RAUSP*

Bull, R., Romanowicz, J., Jennings, N., Laskari, M., Stuart, G., & Everitt, D. (2018). Competing priorities: lessons in engaging students to achieve energy savings in universities. *International Journal of Sustainability in Higher Education*, *19*(7), 1220–1238. https://doi.org/10.1108/IJSHE-09-2017-0157

Chai, C., Zhou, Z., Yin, W., Hurwitz, D. S., & Zhang, S. (2022). Evaluating the moderating effect of in-vehicle warning information on mental workload and collision avoidance performance. *Journal of Intelligent and Connected Vehicles*, *5*(2), 49–62. https://doi.org/10.1108/JICV-03-2021-0003

Chen, C., Landa, S., Padilla, A., & Yur-Austin, J. (2021). Learners' experience and needs in online environments: adopting agility in teaching. *Journal of Research in Innovative Teaching & Learning*, *14*(1), 18–31. https://doi.org/10.1108/JRIT-11-2020-0073

Chongchitpaisan, W., Wiwatanadate, P., Narkpongphun, A., Tanprawate, S., & Siripon, N. (2020). Sleep loss among Thai high school students smartphone users affected by smartphone electromagnetic pollution. *Journal of Health Research*, *34*(4), 317–327. https://doi.org/10.1108/JHR-05-2019-0104

Cressey, J. (2019). Developing culturally responsive social, emotional, and behavioral supports. *Journal of Research in Innovative Teaching & Learning*, *12*(1), 53–67. https://doi.org/10.1108/JRIT-01-2019-0015

David, P., Zulkafli, I. S., Mohd Zamin, R., Samberkar, S., Wong, K. H., Naidu, M., & Das, S. (2024). Video as an interventional tool for bridging the gap in anatomy knowledge of

medical postgraduates. *Arab Gulf Journal of Scientific Research*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/AGJSR-03-2023-0097

Dreisiebner, S., Polzer, A. K., Robinson, L., Libbrecht, P., Boté-Vericad, J.-J., Urbano, C., Mandl, T., Vilar, P., Žumer, M., Juric, M., Pehar, F., & Stričević, I. (2021). Facilitation of information literacy through a multilingual MOOC considering cultural aspects. *Journal of Documentation*, *77*(3), 777–797. https://doi.org/10.1108/JD-06-2020-0099

Errabo, D. D., dela Rosa, A., & Gonzales, L. J. M. (2024). Optimizing differentiated podcasts to promote students' self-regulation and engagement, self-efficacy and performance in asynchronous learning. *Journal of Research in Innovative Teaching & Learning*, *17*(2), 368–390. https://doi.org/10.1108/JRIT-02-2024-0039

Ghosh, C., Gilson, P., & Rakotomavo, M. (2020). Student managed fund (SMF) at the University of Connecticut. *Managerial Finance*, *46*(4), 548–564. https://doi.org/10.1108/MF-09-2018-0426

Gom-os, D. F. K., & Yong, K. Y. (2022). An empirical study on the use of a facial emotion recognition system in guidance counseling utilizing the technology acceptance model and the general comfort questionnaire. *Applied Computing and Informatics*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/ACI-06-2022-0154

Habiba, A., Isnanto, R. R., & Suseno, J. E. (2023). The Effect of Chi Square Feature Selection on the Naïve Bayes Algorithm on the Analysis of Indonesian Society's Sentiment About Face-to-Face Learning During the Covid-19 Pandemic. *JST (Jurnal Sains Dan Teknologi)*, *12*(1), 111-116.

Hamdan, H. (2023). Functions of student code-switching in a Bruneian classroom. *Southeast Asia: A Multidisciplinary Journal*, *23*(1), 55–69. https://doi.org/10.1108/SEAMJ-01-2023-0007

Hesen, R., Wals, A. E. J., & Tauritz, R. L. (2022). Creating a sense of community and space for subjectification in an online course on sustainability education during times of physical distancing. *International Journal of Sustainability in Higher Education*, *23*(8), 85–104. https://doi.org/10.1108/IJSHE-07-2021-0270

Hilletofth, P., Sequeira, M., & Tate, W. (2021). Fuzzy-logic-based support tools for initial screening of manufacturing reshoring decisions. *Industrial Management & Data Systems*, *121*(5), 965–992. https://doi.org/10.1108/IMDS-05-2020-0290

Humanitarian Logistics and Supply Chain Management, *14*(2), 171–180. https://doi.org/10.1108/JHLSCM-04-2022-0047

Ishtaiwa, F. F., & Shana, Z. (2011). The use of interactive whiteboard (IWB) by pre-service teachers to enhance Arabic language teaching and learning. *Learning and Teaching in Higher Education: Gulf Perspectives*, *8*(2), 17–34. https://doi.org/10.18538/lthe.v8.n2.65

Ishtaiwa, F. F., & Shana, Z. (2011). The use of interactive whiteboard (IWB) by pre-service teachers to enhance Arabic language teaching and learningJutz, C., Griese, K.-M., Rau, H., Schoppengerd, J., & Prehn, I. (2024). Of study enthusiasts and homebirds: students' everyday mobility and sustainability dilemmas in online higher education. *International Journal of Sustainability in Higher Education*, *25*(9), 195–212. https://doi.org/10.1108/IJSHE-07-2023-0272

Kaur, P., Dhir, A., Talwar, S., & Alrasheedy, M. (2021). Systematic literature review of food waste in educational institutions: setting the research agenda. *International Journal of Contemporary Hospitality Management*, *33*(4), 1160–1193. https://doi.org/10.1108/IJCHM-07-2020-0672

Kuhnel, M., Seiler, L., Honal, A., & Ifenthaler, D. (2018). Mobile learning analytics in higher education: usability testing and evaluation of an app prototype. *Interactive Technology and Smart Education*, *15*(4), 332–347. https://doi.org/10.1108/ITSE-04-2018-0024

Lau, F. M. F., & Sou, G. (2018). Assessment for learning: Hong Kong needs territory-wide system assessment (TSA) or not. *Public Administration and Policy*, *21*(1), 68–84. https://doi.org/10.1108/PAP-06-2018-004

Leslie, H. J. (2020). Trifecta of Student Engagement. *Journal of Research in Innovative Teaching & Learning*, *13*(2), 149–173. https://doi.org/10.1108/JRIT-10-2018-0024

MacLeod, C. (2015). iPads in the classroom: trials in a technical college in Qatar. *Learning and Teaching in Higher Education: Gulf Perspectives*, *12*(1), 62–95. https://doi.org/10.18538/lthe.v12.n1.170

Management Journal, *56*(1), 24–37. https://doi.org/10.1108/RAUSP-02-2019-0029

Meland, P. H., Bernsmed, K., Frøystad, C., Li, J., & Sindre, G. (2019). An experimental evaluation of bow-tie analysis for security. *Information & Computer Security*, *27*(4), 536–561. https://doi.org/10.1108/ICS-11-2018-0132

Moreno Rocha, O. Y., Pinto, P., Consuegra, M. C., Cifuentes, S., & Ulloa, J. H. (2024). Mobile ultrasound vascular assessment (MUVA) for remote and conflict areas. *Journal of*

Morfaki, C., & Skotis, A. (2023). Academic online learning experience during COVID-19 - a systematic literature review based on personality traits. *Higher Education, Skills and Work-Based Learning*, *13*(4), 697–719. https://doi.org/10.1108/HESWBL-03-2022-0062

Mostafa, M., Sotelo, M., Honsberger, T., Honsberger, C., Brooker Lozott, E., & Shanok, N. (2024). The impact of ASPECTSS-based design intervention in autism school design: a case study. *Archnet-IJAR: International Journal of Architectural Research*, *18*(2), 318–339. https://doi.org/10.1108/ARCH-11-2022-0258

Mourelatos, E., & Manganari, E. (2023). Resilience, vulnerability and personality effects on social commerce intentions: the COVID-19 era. *Young Consumers*, *24*(3), 288–308. https://doi.org/10.1108/YC-04-2022-1515

Ola, B. A., & Morakinyo, O. (2010). Study habits among Nigerian secondary school students with brain fag syndrome. *Mental Illness*, *2*(1), 6–10. https://doi.org/10.4081/mi.2010.e2

Priyashantha, A. K. H., Pratheesh, N., & Pretheeba, P. (2022). Parental perception of distance learning and homeschooling during COVID-19 pandemic: an empirical analysis in Sri Lanka. *Asian Association of Open Universities Journal*, *17*(3), 261–276. https://doi.org/10.1108/AAOUJ-05-2022-0073

Rakús, M., Farkaš, P., & Páleník, T. (2021). Modeling of mobile channels using TIMS in IT education. *Applied Computing and Informatics*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/ACI-04-2021-0089

Rakús, M., Farkaš, P., & Páleník, T. (2021). Modeling of mobile channels using TIMS in IT education. *Applied Computing and Informatics*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/ACI-04-2021-0089

Roberts, K., Benson, A., & Mills, J. (2021). E-textbook technology: Are instructors using it and what is the impact on student learning? *Journal of Research in Innovative Teaching & Learning*, *14*(3), 329–344. https://doi.org/10.1108/JRIT-04-2021-0028

Sequeira, M., Hilletofth, P., & Adlemo, A. (2021). AHP-based support tools for initial screening of manufacturing reshoring decisions. *Journal of Global Operations and Strategic Sourcing*, *14*(3), 502–527. https://doi.org/10.1108/JGOSS-07-2020-0037

Shawky, A., Elbiblawy, E., & Maresch, G. (2021). Spatial ability differences between students with a math learning disability and their other normal colleagues. *Journal of Humanities and Applied Social Sciences*, *3*(3), 182–198. https://doi.org/10.1108/JHASS-01-2020-0016

Srivastava, P., Sehgal, T., Jain, R., Kaur, P., & Luukela-Tandon, A. (2024). Knowledge management during emergency remote teaching: an interpretative phenomenological

analysis of the transition experiences of faculty members. *Journal of Knowledge Management*, *28*(11), 78–105. https://doi.org/10.1108/JKM-02-2023-0112

Staugaard, S. R., & Rosenberg, N. K. (2011). Processing of emotional faces in social phobia. *Mental Illness*, *3*(1), 14–20. https://doi.org/10.4081/mi.2011.e5

Sulaksono, N., Adi, K., Isnanto, R., & Warsito, B. (2023, April). Uretery Stone Detection with CT Scan Image Contrast Analysis. In *Proceeding of the 3rd International Conference on Electronics, Biomedical Engineering, and Health Informatics: ICEBEHI 2022, 5–6 October, Surabaya, Indonesia* (pp. 163-171). Singapore: Springer Nature Singapore.

Tanglakmankhong, K., Hampstead, B. M., Ploutz-Snyder, R. J., & Potempa, K. (2022). Cognitive screening assessment in Thai older adults: a prospective study of the reliability and validity of the Abbreviated Mental Test. *Journal of Health Research*, *36*(1), 99–109. https://doi.org/10.1108/JHR-02-2020-0049

Tattersall Wallin, E. (2022). Audiobook routines: identifying everyday reading by listening practices amongst young adults. *Journal of Documentation*, *78*(7), 266–281. https://doi.org/10.1108/JD-06-2021-0116

Thakker, S. V., Parab, J., & Kaisare, S. (2021). Systematic research of e-learning platforms for solving challenges faced by Indian engineering students. *Asian Association of Open Universities Journal*, *16*(1), 1–19. https://doi.org/10.1108/AAOUJ-09-2020-0078

Uehara, T., & Ishige, Y. (2015). Bipolar mood tendency and frontal activation using a multichannel near infrared spectroscopy. *Mental Illness*, *7*(2), 36–41. https://doi.org/10.1108/mi.2015.5767

Umemiya, N., Sugimura, M., Kosaikanont, R., Nordin, N. M., & Ahmad, A. L. (2024). Impact of a consortium-based student mobility programme: The case of AIMS (Asian International Mobility for students). *Journal of International Cooperation in Education*, *26*(1), 49–66. https://doi.org/10.1108/JICE-08-2023-0020

van de Ven, N., Bogaert, A., Serlie, A., Brandt, M. J., & Denissen, J. J. A. (2017). Personality perception based on LinkedIn profiles. *Journal of Managerial Psychology*, *32*(6), 418–429. https://doi.org/10.1108/JMP-07-2016-0220

Westermann, F., Doll, L., Duprés, M., Späth, S., & Schweizer-Ries, P. M. (2021). Overcoming physical distancing in online communities to create human spaces for societal transformations. *Journal of Work-Applied Management*, *13*(2), 197–214. https://doi.org/10.1108/JWAM-03-2021-0023

Wright, N. S., Redding, R., & Eltom, M. (2007). Online Quizzes: A Self-Conscious Exploration of Strategic Trade-offs in the Middle East. *Learning and Teaching in Higher Education: Gulf Perspectives*, *4*(2), 2–10. https://doi.org/10.18538/lthe.v4.n2.05

Yin, K., Cao, Y., Zhou, S., & Lv, X. (2022). Research on optimization of index system design and its inspection method: data quality diagnosis, index classification and stratification. *Marine Economics and Management*, *5*(2), 105–146. https://doi.org/10.1108/MAEM-05-2022-0005