Journal of Computer and Education Research
April 2022 Volume 10 Issue 19
http://dergipark.org.tr/jcer
(ISSN:2148-2896)

Research Article

The Current Trend in Educational Neuroscience Research: A Descriptive and Bibliometric Study

Şenol SAYGINER [1] Fatih BALAMAN *[2] Sevil HANBAY TİRYAKİ [3]

[1] *Hatay Mustafa Kemal University, Faculty of Education, Hatay, Turkey, senolsayginer@gmail.com*
[2] *Hatay Mustafa Kemal University, Faculty of Education, Hatay, Turkey, fatihbalaman2010@gmail.com*
[3] *Doctoral Student, Institute of Science, Hatay Mustafa Kemal University, Hatay, Turkey, sevilhanbay90@gmail.com*

**Corresponding Author: fatihbalaman2010@gmail.com*

Article Info

Received: *30 September 2021*
Accepted: *1 April 2022*

Keywords: Educational neuroscience, neuroimaging, EEG, bibliometric analysis

10.18009/jcer.1002588

Publication Language: English

Abstract

In the present study, 36 articles indexed in the Web of Science database were examined in order to reveal the current trend in scientific studies in the field of educational neuroscience. Therefore, the distribution of the articles was examined considering publication years, host journals, the most productive author(s), co-authorship, abstract keywords, collocated keywords, educational attainment of the samples, dependent variables, and the EEG devices used. The data were evaluated with descriptive and bibliometric analysis methods. The findings revealed that the publishing in the field gained an elevation in 2020; the papers were mostly published in Computers & Education; Mayer was the most productive author; Cheng, Lin, Yang, and Huang were those who produced the most collaborative studies in the field. In addition, it was found out that the keyword "cognitive load" was discussed more than the others; it was used with "attention" the most; studies were mostly carried out at university level; cognitive load and attention were the most examined dependent variables; the NeuroSky Mindwave was used in these articles the most. To sum, the present results have the potential to generate an overall perspective to educational neuroscience.

To cite this article: Saygıner, Ş., Balaman, F., & Hanbay-Tiryaki, S. (2022). The current trend in educational neuroscience research: A descriptive and bibliometric study. *Journal of Computer and Education Research, 10* (19), 184-201. https://doi.org/10.18009/jcer.1002588

Introduction

How students think and how learning occurs are seminal topics discussed much in education. In this regard, scholars carry out interdisciplinary research to understand the nature of learning and identify the synaptic connections during an activity, the active regions in the brain, and the relationship of these regions with each other. Ultimately, neuroscience provides a basis for such research: it serves to explain structural and functional features of the human nervous system as a branch of science examining its physiology (function), anatomy (structure), biochemistry (chemical substances in nerve cells and tissue), and biology (formation/development) (Deryakulu et al., 2019).

One may have many changes in their brain when learning, and such changes are primarily explained in the focus of cognitive or educational neuroscience. Cognitive neuroscience studies the function of the brain as a biological organ. In other words, cognitive neuroscience is concerned with which parts of the human brain work how during any problem-solving activity (Ansari et al., 2011). The relevant research focuses on examining the brain activities and various neurological patterns of individuals with typical development or various learning difficulties. In this respect, it can be asserted that cognitive neuroscience mediates neuroscience to inform the field of education and directs educational research. In fact, cognitive neuroscience research has recently started to attract the attention of educators. In particular, the topic of how to integrate the data revealed by cognitive neuroscience research with the learning process has given rise to educational neuroscience research.

In the words of Schunk (2012), the integration of knowledge on how the brain, a fascinating, central organ of learning, works and learns and the results of cognitive neuroscience research into educational settings constitutes the general framework of educational neuroscience (neuroeducation or mind-brain-education). Educational neuroscience research attempts to expound learning and development processes based on brain functioning (Ferrari, 2011). The relevant research shows that awareness of how learning occurs in the brain will contribute to directing, managing, and structuring own learning (Duman, 2015). Such potential contributions highlight the rising trend of neuroscience research in the educational context.

Educational neuroscience research is mainly interested in cutting-edge educational technologies and systems. Put another way, the research aims to directly engage in exploring brain functions instead of/as well as self-report-oriented data collection processes (Varma et al., 2008). Thus, researchers may use techniques allowing visualization of mobility in the brain, such as Functional Magnetic Resonance Imaging (fMRI), Magnetic Resonance Imaging (MRI), and Magnetoencephalogram (MEG), without resorting to any surgical procedure. On the other hand, another technique is the Electroencephalogram (EEG), which is frequently preferred in educational research for its cost-effectiveness and convenience.

EEG is a test where neural activity is measured with electrodes placed on the scalp (Koçak, 2020) and attempts to examine brain functions directly (Varma et al., 2008). The studies where EEG is used consider brain waves varying by actions. Brain waves are divided by their frequencies: gamma, beta, alpha, theta, and delta (Tabakcıoğlu et al., 2016). Alpha (8-

13 Hz), beta (13-30 Hz), and theta (4-7 Hz) waves are the most prevalent ones in educational neuroscience research (Yazgan & Korurek, 1996). In the tests, varying EEG devices may be used to detect signals from the brain waves (Morshad et al., 2020). In this regard, EEG-based neuroimaging devices, such as Neurosky Mindwave, Emotiv EPOC, or B-Alert, offer functional features that can be used in an educational context.

Research in educational neuroscience scrutinizes the impacts of many factors on learning and explores complex processes such as language, speech, reading, perception, thinking, reasoning, and problem-solving (Dündar, 2013; Varma et al., 2008). In this regard, the present study aimed to examine such studies by various variables and present an evaluation of the current trend in educational neuroscience. It is expected that the present findings would draw a general framework for educational neuroscience and guide further studies. Ultimately, the present research sough answers to the following questions:

1. Articles in the field of educational neuroscience

1.1. How is the distribution of the articles by their publication years?

1.2. How is the distribution of the articles by host journals?

2. In the field of educational neuroscience

2.1. How is the distribution of the most productive researchers?

2.2. How is the distribution of the researchers by co-authorship?

3. Articles in the field of educational neuroscience

3.1. How is the distribution of the keywords?

3.2. How is the distribution of the co-used keywords?

4. How is the distribution of the samples in these articles by their educational attainment?

5. What are the dependent variables covered in articles in the field of educational neuroscience?

6. What are the EEG technologies used to display brain waves in articles in the field of educational neuroscience?

Method

The present research aimed to review the studies in the field of educational neuroscience and to classify the data related to these studies by various variables. The research was carried out using bibliometric analysis and descriptive analysis. Utilizing these techniques, it is was primarily attempted to create visual presentations, increase the readability and clarity of the findings, make comparisons easier, and determine the relationships between the study variables.

Selection of Manuscripts

The ISI Web of Knowledge (WOS) database was utilized to obtain original manuscripts on educational neuroscience. The keywords "electroencephalography, EEG, education" were used in the queries through the specified database. However, the research outside the field of education, unpublished studies, and closed-door articles were not considered in the analyses. Thus, a total of 36 articles matching the purpose of the research were included in the study.

Data Analysis

Both bibliometric and descriptive analyses were used in this study. The bibliometric analysis was performed using the VOSviewer software, a visualization tool for creating network graphics of the publications (Iron & Power, 2018). The software also allows the user to dig into keywords or co-authorship within the publications studied.

On the other hand, the thematic variables in the study were investigated through descriptive analysis. The relevant data were presented in tables and charts based on frequency distributions. Besides, an "article review form" was created to address the descriptive data more systematically. The form includes columns for title, year of publication, hots journal, researcher information, keywords, sample, dependent variables covered, and EEG tools used.

Three researchers separately carried out the article review process. The statements by each researcher in the article review forms were also checked by other researchers, and written suggestions were given for possible contradictions. Then, the researchers came together and tried to reach a consensus on each other's opinions. In addition, two experts with a Ph.D. degree in Computer Education and Instructional Technologies reviewed the coding, and uncertainties in the coding were discussed and settled.

Findings

This section presents the findings in order by the sub-questions above.

Findings regarding publication years and host journals of the papers

Figure 1 presents the distribution of 36 papers on brain waves in educational contexts by their publication years.

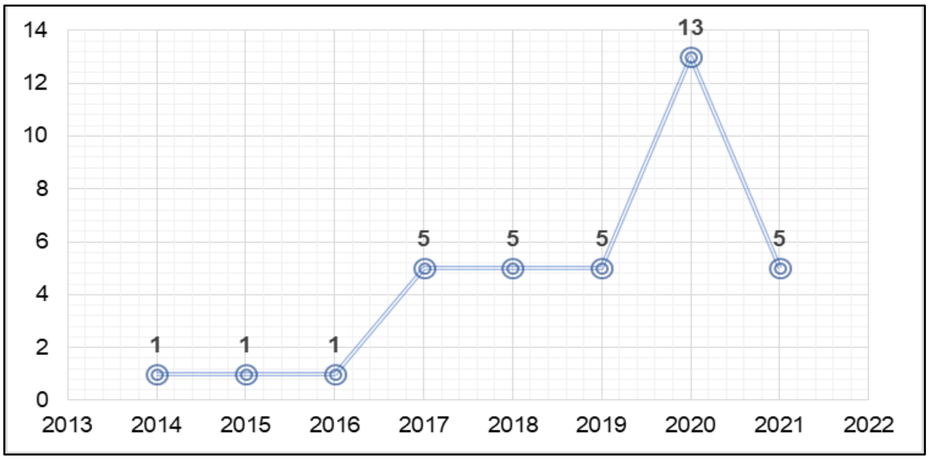


Figure 1. Distribution of the papers by publication years

The graph clearly demonstrates a linear increase in the number of studies in the relevant field over time. While 2014 is the year when the fewest papers were published (only one), 2020 witnessed a plethora of studies with 13 publications. The reason for the low rate of publications in 2021 may be because only those published in the first seven months of the year were considered in this study.

Figure 2 illustrates the frequency of 36 papers on brain waves in educational contexts by their host journals.

Figure 2. Distribution of the papers by host journals

Figure 2 shows that the related papers were mostly published in Computers & Education (4). It is followed by Educational Technology & Society (3), Educational Technology Research and Development (3), Journal of Computer Assisted Learning (3), BJET (2), Education and Information Technologies (2), and Interactive Learning Environments (2), respectively.

Findings Regarding Authors

Table 1 delivers the 10 top productive authors on brain waves in educational contexts.

Table 1. Distribution of authors by productivity

	Authors	Number of articles	Total cited	Country	Affiliate (University)
1	Mayer, R.E.	3	158	USA	University of California Santa Barbara
2	Huang Y.M.	3	42	Taiwan	National Cheng Kung University
3	Cheng, PY	3	31	China	Capital Medical University
4	Yang, X.Z.	3	31	Japan	Osaka University
5	Lin, L.	3	31	USA	University of North Texas Denton
6	Makransky, G.	2	151	Denmark	University of Copenhagen
7	Terkildsen, T.	2	151	Denmark	University of Copenhagen
8	Ren, YQ	2	31	China	East China Normal University
9	Yang, X.	2	24	USA	University of North Texas Denton
10	Parong, J.	2	9	USA	University of California Santa Barbara

It was found that the prominent authors by the number of publications are Mayer (3), Huang (3), Cheng (3), Yang (3), and Lin (3). Besides, when considering the total number of citations to their publications, Mayer (158) was discovered to be the most cited author. On the other hand, although they did fewer publications, Makransky (151) and Terkildsen (151) are among the most cited researchers following Mayer.

It was also sought which authors did collaborative works the most. The findings were examined using VOSviewer software, and Figure 3 presents the distribution of the authors by co-authorship.

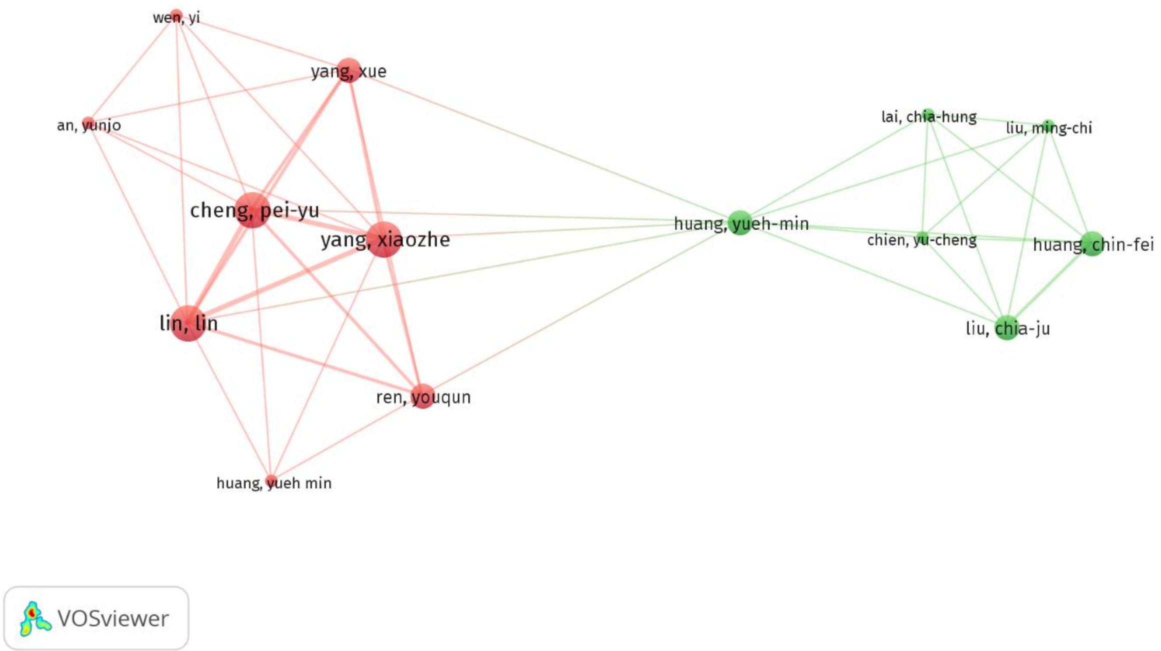


Figure 3. Distribution of authors by co-authorship

The co-authorship situation was identified considering the thinness-thickness status of the connections between the authors and the clustering density of these connections. Therefore, it was determined that the authors engaging in co-authorship the most are Cheng, Lin, Yang, and Huang. In other words, the distribution in Table 1 reveals that these researchers acted collaboratively despite being in different countries and institutions.

Findings regarding keywords

The keywords were gone through to be informed about the scopes of the articles. Figure 4 shows which keywords are used the most in the papers.

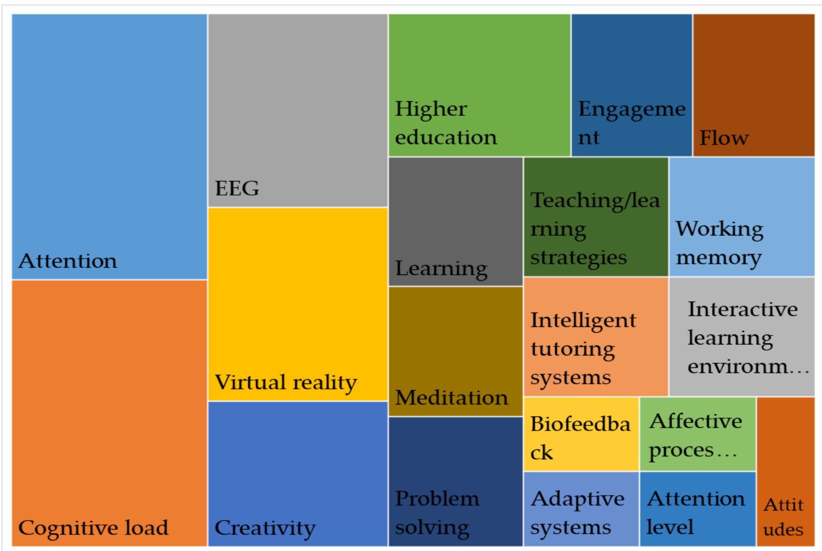


Figure 4. Distribution of the most frequent keywords

Figure 4 reveals that the most frequent keyword is cognitive load, which is followed by attention, virtual reality, EEG, higher education, interactive learning environments, intelligent tutoring systems, working memory, learning/teaching strategies, problem-solving, meditation, learning, flow, engagement, affective process, adaptive systems, and feedback.

Besides, Figure 5 demonstrates which of these keywords are collocated more.

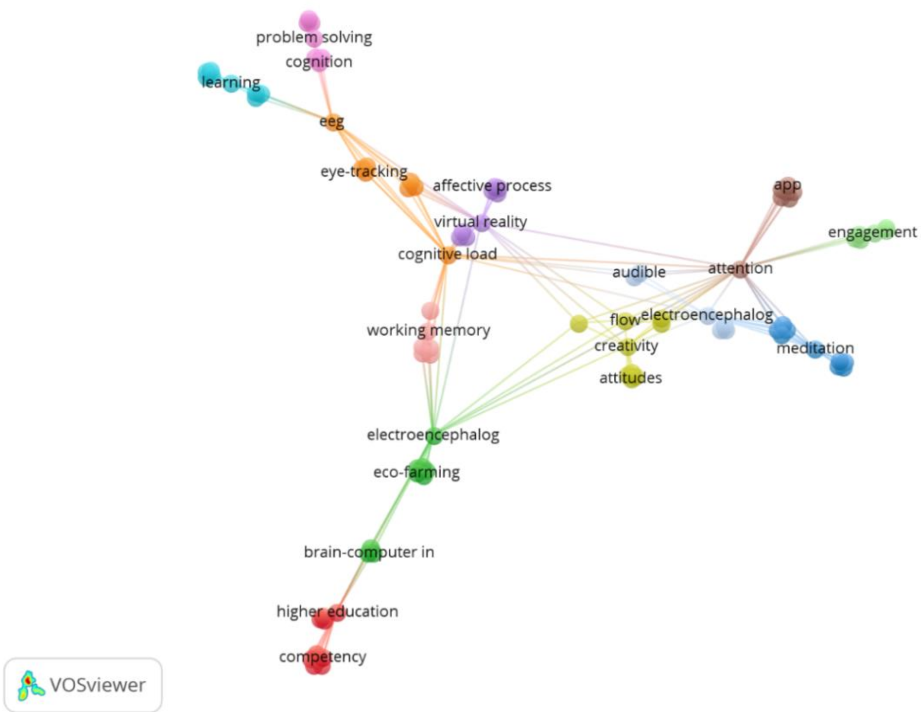


Figure 5. Distribution of collocated keywords

It was found that the most common keyword, "cognitive load," is collocated chiefly with the words "attention, working memory, and virtual reality." Moreover, the keyword "attention" is mostly collocated with "cognitive load, meditation, engagement, flow, and virtual reality." When it comes to the keyword "virtual reality," it was discovered to be frequently collocated with the keywords "cognitive load, attention, flow, creativity, and emotional processes."

Findings Regarding Samples in the Papers

In another research question, it was enquired about the educational attainment of the samples who underwent the experimental processes in these 36 studies. Figure 6 shows the obtained findings.

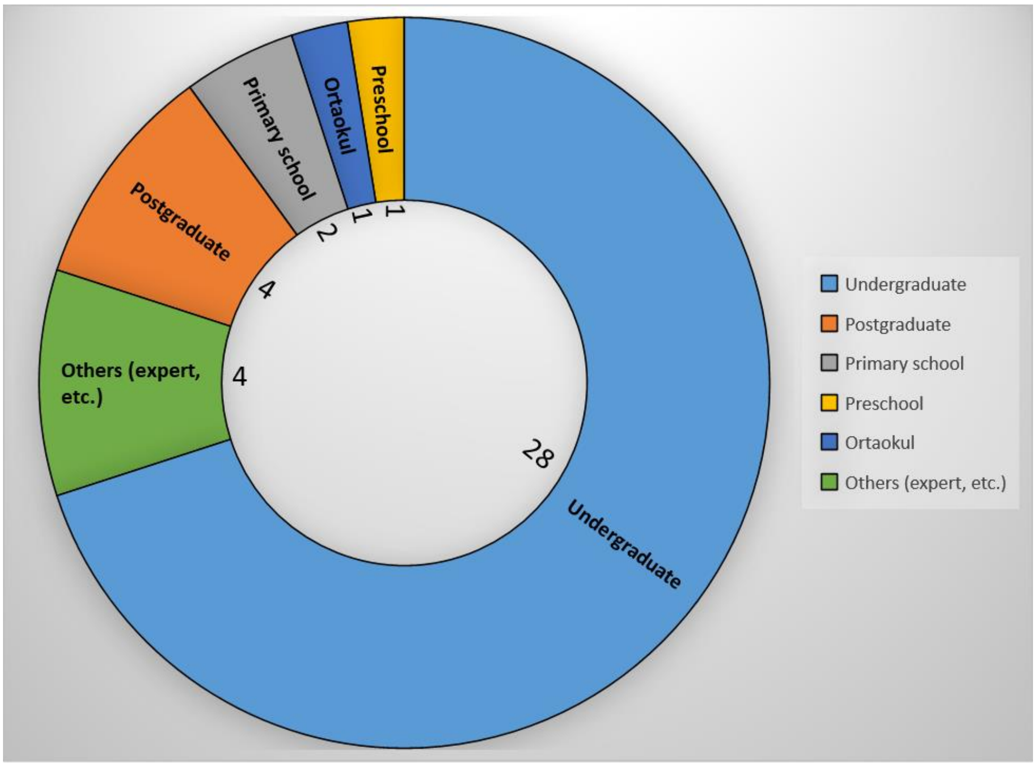


Figure 6. Distribution of samples by their educational attainment

It was noted that the authors performed the data collection processes mainly at the university level (28), which is followed by postgraduate (4), primary school (2), secondary school (1), and preschool (1) levels, respectively. Consequently, it may be implied that studies are more limited at low ages and grades.

Findings Regarding Dependent Variables in the Articles

The dependent variables discussed in the articles were also noted. Thereby, the most included dependent variables are listed in Figure 7.

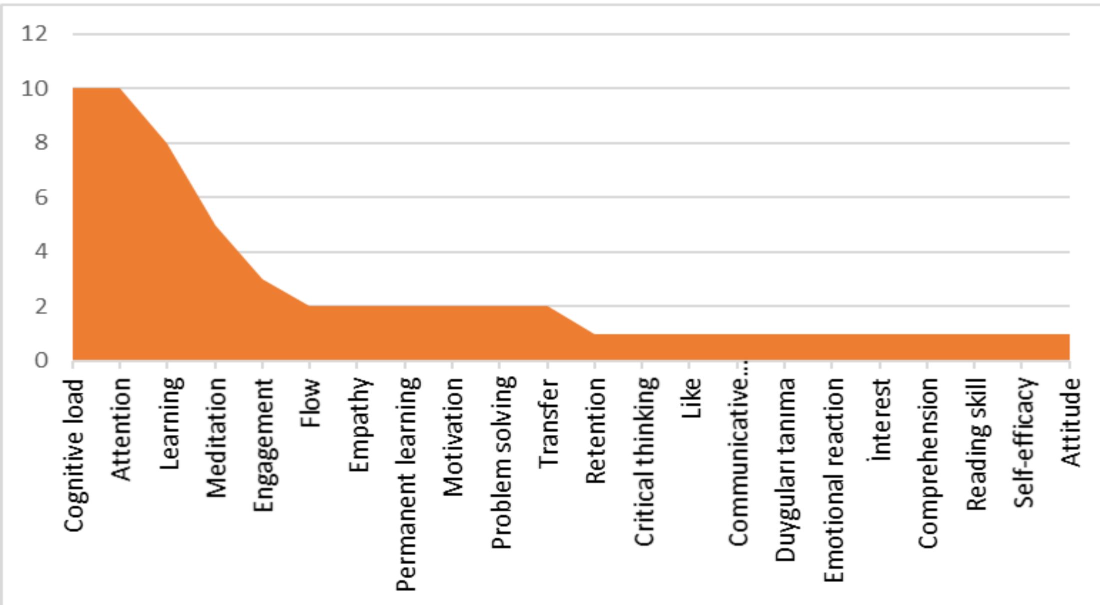


Figure 7. Distribution of dependent variables in the articles

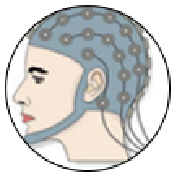
It was found that the most investigated variables are cognitive load (10) and attention level (10), which are followed by learning (8), meditation (5), engagement level (3), and flow (2), respectively.

Findings Regarding EEG Technologies for Monitoring Brain Waves

Table 2 summarizes EEG devices for monitoring brain waves in the papers.

Table 2. EEG devices for monitoring brain waves

EEG device	NeuroSky Mindwave	Emotiv EPOC	B-Alert X10	Electrode cap	ActiCHamp EEG	ANT Neuro EEGO
Frequency	***12***	***5***	***4***	***1***	***1***	***1***
Image						

EEG device	DSI 24 EEG	Headband InteraXon Muse	EEG:G.TEC G.Nautilus	Emotiv EEG 32 kanallı	Mitsar EEG	NeuroScan SynAmps RT
Frequency	***1***	***1***	***1***	***1***	***1***	***1***
Image						

EEG device	NeuroSky MindBand	NeuroSky's Mindset	Other
Frequency	***1***	***1***	***4***
Image			

(From: Vourvopoulos & Liarokapis (2012), Ekanayake (2010), Chew et al. (2016), Fiedler et al. (2015), Barraza et al. (2019), Causa et al. (2018), Soufineyestani et al. (2020), Sanchez-Cifo et al. (2021), Yoghourdjian et al. (2020), Emotiv (2018), Deuel et al. (2017), Mahajan et al. (2014), Ma & Wei (2016), Guomundsdoottir (2011), respectively.)

NeuroSky Mindwave was noticed to be the most frequently used EEG device in the studies (12). The device bears an apparatus attaching to the head and ear and can produce attention and meditation data through its single channel. Emotiv EPOC (5) and B-Alert (4) systems came second and third, respectively. Two other EEG tools (Mindband and Mindset) from Neurosky were the least utilized technologies in the research.

Discussion

In this study, uncovering the overall picture and trends in educational neuroscience, 36 articles were reviewed by some relevant variables. In the review, it was found out that the first publication in educational neuroscience was released in 2014, while the highest number of publications (13) belongs to 2020, which clearly informs that the field has attracted attention of authors over time. Yet, it may be assert that the relatively small number of studies in 2021 may have resulted from the inclusion of only studies published in the first seven months of 2020 and the disruptions in data collection processes due to the ongoing COVID-19 pandemic. On the other hand, the articles were primarily published in Computers & Education magazine; the fact that this journal is among the leading journals in educational technologies may indicate that educational neuroscience ranks among the timely and important topics.

Other findings were for the most productive authors in the field and those engaged in co-authorship. In this context, Richard Mayer was the author who came first with the most studies. Educational neuroscience is at the center of three pillars of psychology, education, and neuroscience (Feiler & Stabio, 2018). Thanks to his expertise in psychology, Mayer produced studies designed with his theories on cognition and learning and presented current perspectives to educational neuroscience, which may be confirmed with the number of citations to his works. On the other hand, Cheng (China), Lin (USA), Yang (Japan), and Huang (Taiwan) stand out in co-authorship. Although these authors are from different countries and institutions, they were able to produce collaborative studies successfully. Therefore, this situation may indicate that it is likely to conduct a large number of studies in educational neuroscience and examine the field in-depth in different conditions and cultures without borders.

The most frequently used and collocated keywords were also reviewed to obtain more detailed information on the scopes of the recruited articles. Findings revealed that the most frequently used keywords are cognitive load and attention, respectively. The literature suggests that cognitive load cannot be observed directly because it is linked with the internal processes of information processing (İkiz, 2021), and physiological methodologies, such as EEG, may be used for more objective measurements of cognitive load (Sweller et al., 2019). Besides, cognitive load is mostly collocated with attention; it can be asserted that one of the most noteworthy factors generating cognitive load is attention. Considering the limited cognitive capacity of humans, if a student is forced to look at both an animation and text within a material presented, the effect of divided attention will emerge (Çakmak, 2007); therefore, divided attention is likely to elevate cognitive load (Sweller, 2004). This situation may explain why cognitive load was frequently addressed through attention in the articles.

It was realized that the authors mostly collected their data at the university level and that studies gathering data from lower graders are somewhat limited. Data collection tools in educational neuroscience may not be convenient at lower grades due to challenges in official permissions (parents, ethics, etc.) and possible difficulties in data collection (external variables, such as mobility or inability to focus, may distort data collection). Put another way, data collection and analysis may be more difficult in research with younger age groups or lower graders. However, despite such disadvantages, Wu and Kim (2019) conducted studies with preschool groups. In order to eliminate these disadvantages, they used the ActiCHamp EEG device, an EEG technology with a large number of channels and similar to the header type.

Cognitive load and attention are the dependent variables discussed more than the others; a similar result was obtained in the analysis of keywords. This situation may be related to the fact that the studies preferred NeuroSky Mindwave the most since the device can obtain data through only a single channel. One may obtain data only for attention, focus, meditation, and stress from the prefrontal cortex. Therefore, the articles may have used the data for attention and meditation to explain cognitive load.

The most commonly used EEG device in the reviewed articles was found to be NeuroSky Mindwave, which may be explained with its or similar devices' practical and easy-to-use nature. Compared to its counterparts, the device does not need to apply the gel on participants' heads or electrodes. In contrast, such a "gel" requirement may bring more limitations on parental consent, especially in younger age groups. On the other hand, why the Emotiv EPOC is less preferred compared to the NeuroSky Mindwave may be because it requires more expertise and cost in the data analysis.

Limitations

Our findings are limited to the query using relevant keywords and the articles in the WOS database. Further studies may access new articles by querying diverse keywords in larger and more comprehensive databases. On the other hand, the data were analyzed using bibliometric analysis. Before the VOSviewer software extracts the data from WoS, the process of making some adjustments to the program and making the data suitable for analysis requires substantial attention and time, which may be considered a limitation for this and similar studies in the literature (Gürlen et al., 2018).

Conclusion and Recommendations

Overall, 36 articles in educational neuroscience were reviewed by various variables. In the study, it was concluded that NeuroSky Mindwave technology was the most used tool within the scope of EEG research and that the studies reviewed were mostly carried out at the university level. Cognitive load, attention, learning, and meditation were found to be the most emphasized variables. With reference to these results, some suggestions for future research are made below:

- It was attempted to investigate the associations between the variables in the study, yet it remained limited with the relationship between two variables included in the model. Further studies may reach more comprehensive findings by having more variables in the model and establishing cross-relationships.
- One may recruit a much larger number of samples in bibliometric analysis studies and reveal a more apparent trend on the subject. Thus, prospective researchers may conclude more comprehensive findings using diverse databases and bibliometric analysis software.

Our findings revealed that educational neuroscience is mainly studied at the university level. The subject may need to be scrutinized at pre-university levels.

Acknowledgement

Due to the scope and method of the study, ethics committee permission was not required.

Author Contribution Statement

Şenol SAYGINER: *Data analysis, data collection, review and editing.*

Fatih BALAMAN: *Methodology, data analysis, review-writing and editing.*

Sevil HANBAY TİRYAKİ: *Writing literature, introduction, data analysis.*

References

Ansari, D., Coch, D., & De Smedt, B. (2011). Connecting education and cognitive neuroscience: Where will the journey take us?. *Educational philosophy and theory*, *43*(1), 37-42. https://doi.org/10.1111/j.1469-5812.2010.00705.x

Çakmak, E. K. (2007). The bottle neck in multimedia: Cognitive overload. *Gazi University Gazi The Journal of Educational Faculty*, *27*(2), 1-24. http://www.gefad.gazi.edu.tr/en/pub/issue/6750/90766

Deryakulu, D., Atal, D., ve Sancar, R. (2019). Eğitimsel sinirbilim ve eğitim teknolojisi açısından doğurguları. (Editörler: A. İşman, H. F. Odabaşı ve B. Akkoyunlu). Eğitim Teknolojileri Okumaları 2019 içinde (ss. 331-348). Pegem Akademi.

Duman, B. (2015). *Neden beyin temelli öğrenme?* Pegem Akademi.

Dündar, S., (2013). *The investigation of students' brain waves in the problem solving process* (Unpublished Doctoral Dissertation). Gazi University.

Feiler, J. B., & Stabio, M. E. (2018). Three pillars of educational neuroscience from three decades of literature. *Trends in neuroscience and education*, *13*, 17-25. https://doi.org/10.1016/j.tine.2018.11.001

Ferrari, M. (2011). What can neuroscience bring to education?. *Educational Philosophy and Theory*, *43*(1), 31-36. https://doi.org/10.1111/j.1469-5812.2010.00704.x

Gürlen, E., Özdiyar, Ö., & Şen, Z. (2018). Social network analysis of academic studies on gifted people. *Education and Science*, *44*(197), 185-208. http://dx.doi.org/10.15390/EB.2018.7735

İkiz, Y. D. (2021). *An investigation of cognitive load effect using augmented reality glasses in an automotive assembly line* (Unpublished Master Dissertation). Bursa Uludağ University.

Koçak, G. (2020). Reflections of brain researches to education: Toward education of future. *Yeditepe University the Journal of Educational Faculty*, *9*(11), 1-16. https://dergipark.org.tr/tr/pub/edu7/issue/59006/731860

Morshad, S., Mazumder, M. R., & Ahmed, F. (2020, January). Analysis of brain wave data using Neurosky Mindwave Mobile II. In *Proceedings of the International Conference on Computing Advancements* (pp. 1-4). https://doi.org/10.1145/3377049.3377053

Sweller, J. (2004). Instructional design consequences of an analogy between evolution by natural selection and human cognitive architecture. *Instructional Science, 32*, 9-31. https://www.jstor.org/stable/41953635

Sweller, J., van Merrienboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review. 31*, 261-292. https://doi.org/10.1007/s10648-019-09465-5

Tabakcıoğlu, M., Çizmeci, H., & Ayberkin, D. (2016). Neurosky EEG biosensor using in education. *International Journal of Applied Mathematics Electronics and Computers*, 76-78. https://doi.org/10.18100/ijamec.265371

Varma, S., McCandliss, B. D., & Schwartz, D. L. (2008). Scientific and pragmatic challenges for bridging education and neuroscience. *Educational researcher, 37*(3), 140-152. https://doi.org/10.3102/0013189X08317687

Yazgan, E., & Korurek, K. M., (1996). *Tıp elektroniği.* İ.T.Ü. Matbaası.

Referances of Studies Examined

Baceviciute, S., Terkildsen, T., & Makransky, G. (2021). Remediating learning from non-immersive to immersive media: Using EEG to investigate the effects of environmental embeddedness on reading in *Virtual Reality. Computers & Education, 164*, 15. https://doi.org/10.1016/j.compedu.2020.104122

Castro-Meneses, L. J., Kruger, J. L., & Doherty, S. (2020). Validating theta power as an objective measure of cognitive load in educational video. *Etr&D-Educational Technology Research and Development, 68*(1), 181-202. https://doi.org/10.1007/s11423-019-09681-4

Chen, C. M., Wang, J. Y., & Yu, C. M. (2017). Assessing the attention levels of students by using a novel attention aware system based on brainwave signals. *British Journal of Educational Technology*, *48*(2), 348-369. https://doi.org/10.1111/bjet.12359

Cuesta-Cambra, U., Nino-Gonzalez, J. I., & Rodriguez-Terceno, J. (2017). The cognitive processing of an educational app with electroencephalogram and "Eye Tracking". *Media Education Research Journal*, *25*(52), 41-50. https://doi.org/10.3916/c52-2017-04

Dan, A., & Reiner, M. (2018). Reduced mental load in learning a motor visual task with virtual 3D method. *Journal of Computer Assisted Learning*, *34*(1), 84-93. https://doi.org/10.1111/jcal.12216

Delahunty, T., Seery, N., & Lynch, R. (2020). Exploring problem conceptualization and performance in STEM problem solving contexts. *Instructional Science*, *48*(4), 395-425. https://doi.org/10.1007/s11251-020-09515-4

Eldenfria, A., & Al-Samarraie, H. (2019). The effectiveness of an online learning system based on aptitude scores: An effort to improve students' brain activation. *Education and Information Technologies*, *24*(5), 2763-2777. https://doi.org/10.1007/s10639-019-09895-2

Ferreira, A. C., Santiago, M. A., & Ortega, M. D. L. (2021). Use of BCI devices in students for teacher assessment. *Ried-Revista Iberoamericana De Educacion a Distancia*, *24*(1), 315-328. https://doi.org/10.5944/ried.24.1.27502

Hu, L. J., Xie, Y. J., & Sun, G. X. (2018). Computer-aided cognitive training based on electroencephalography-neurofeedback for English learning. *Educational Sciences-Theory & Practice*, *18*(5), 2593-2601. https://doi.org/10.12738/estp.2018.5.002

Huang, H. W., King, J. T., & Lee, C. L. (2020). The new science of learning: using the power and potential of the brain to inform digital learning. *Educational Technology & Society*, *23*(4), 1-13. https://scholars.cityu.edu.hk/en/publications/publication(5299e970-a4d6-4244-8000-e2535919ed45).html

Kadar, M., Borza, P. N., Romanca, M., Iordachescu, D., & Iordachescu, T. (2017). Smart testing environment for the evaluation of students' attention. *Interaction Design and Architectures*, 32, 205-217. http://www.mifav.uniroma2.it/inevent/events/idea2010/doc/32_13.pdf

Lambert, S., Dimitriadis, N., Taylor, M., & Venerucci, M. (2021). Understanding emotional empathy at postgraduate business programmes: what does the use of EEG reveal for future leaders? *Higher Education Skills and Work-Based Learning*, 12. https://doi.org/10.1108/heswbl-09-2020-0218

Lee, H. (2014). Measuring cognitive load with electroencephalography and self-report: focus on the effect of English-medium learning for Korean students. *Educational Psychology*, *34*(7), 838-848. https://doi.org/10.1080/01443410.2013.860217

Lin, F. R., & Kao, C. M. (2018). Mental effort detection using EEG data in E-learning contexts. *Computers & Education*, *122*, 63-79. https://doi.org/10.1016/j.compedu.2018.03.020

Liu, C. J., Huang, C. F., Liu, M. C., Chien, Y. C., Lai, C. H., & Huang, Y. M. (2015). Does gender influence emotions resulting from positive applause feedback in self-assessment testing? *Evidence from Neuroscience. Educational Technology & Society*, *18*(1), 337-350. https://eric.ed.gov/?id=EJ1062511

Ma, M. Y., & Wei, C. C. (2016). A comparative study of children's concentration performance on picture books: age, gender, and media forms. *Interactive Learning Environments*, *24*(8), 1922-1937. https://doi.org/10.1080/10494820.2015.1060505

Makransky, G., Terkildsen, T. S., & Mayer, R. E. (2019). Adding immersive virtual reality to a science lab simulation causes more presence but less learning. *Learning and Instruction*, *60*, 225-236. https://doi.org/10.1016/j.learninstruc.2017.12.007

Moreno, M., Schnabel, R., Lancia, G., & Woodruff, E. (2020). Between text and platforms: A case study on the real-time emotions & psychophysiological indicators of video gaming and academic engagement. *Education and Information Technologies, 25*(3), 2073-2099. https://doi.org/10.1007/s10639-019-10031-3

Mutlu-Bayraktar, D., Ozel, P., Altindis, F., & Yilmaz, B. (2020). Relationship between objective and subjective cognitive load measurements in multimedia learning. *Interactive Learning Environments, 13*. https://doi.org/10.1080/10494820.2020.1833042

Pajk, T., Van Isacker, K., Abersek, B., & Flogie, A. (2021). STEM Education in eco-farming supported by ICT and mobile applications. *Journal of Baltic Science Education, 20*(2), 277-288. https://doi.org/10.33225/jbse/21.20.277

Parong, J., & Mayer, R. E. (2021a). Cognitive and affective processes for learning science in immersive virtual reality. *Journal of Computer Assisted Learning, 37*(1), 226-241. https://doi.org/10.1111/jcal.12482

Parong, J., & Mayer, R. E. (2021b). Learning about history in immersive virtual reality: does immersion facilitate learning? *Etr&D-Educational Technology Research and Development, 19*. https://doi.org/10.1007/s11423-021-09999-y

Pi, Z. L., Zhang, Y., Zhou, W. C., Xu, K., Chen, Y. R., Yang, J. M., & Zhao, Q. B. (2021). Learning by explaining to oneself and a peer enhances learners' theta and alpha oscillations while watching video lectures. *British Journal of Educational Technology, 52*(2), 659-679, Article e13048. https://doi.org/10.1111/bjet.13048

Robinson, K., Wehner, T., & Millward, H. (2019). Is the outcome of remote group work using text based CMC suboptimal? A psychobiological perspective. *Computers & Education, 134*, 108-118. https://doi.org/10.1016/j.compedu.2019.02.009

Sezer, A., Inel, Y., Seckin, A. C., & Ulucinar, U. (2017). The relationship between attention levels and class participation of first-year students in classroom teaching departments. *International Journal of Instruction, 10*(2), 55-68. https://doi.org/10.12973/iji.2017.1024a

Stockman, C. (2020). Can a technology teach meditation? Experiencing the EEG headband interaxon muse as a meditation guide. *International Journal of Emerging Technologies in Learning, 15*(8), 83-99. https://doi.org/10.3991/ijet.v15i08.12415

Sun, J. C. Y., & Yeh, K. P. C. (2017). The effects of attention monitoring with EEG biofeedback on university students' attention and self-efficacy: The case of anti-phishing instructional materials. *Computers & Education, 106*, 73-82. https://doi.org/10.1016/j.compedu.2016.12.003

Wang, C. Y. (2020). Differences in perception, understanding, and responsiveness of product design between experts and students: an early event-related potentials study. *International Journal of Technology and Design Education, 23*. https://doi.org/10.1007/s10798-020-09592-z

Wang, J. H., Antonenko, P., Keil, A., & Dawson, K. (2020). Converging subjective and psychophysiological measures of cognitive load to study the effects of instructor-present video. *Mind Brain and Education, 14*(3), 279-291. https://doi.org/10.1111/mbe.12239

Wu, L., & Kim, M. (2019). See, touch, and feel: Enhancing young children's empathy learning through a tablet game. *Mind Brain and Education, 13*(4), 341-351. https://doi.org/10.1111/mbe.12218

Wu, S. F., Lu, Y. L., & Lien, C. J. (2021). Detecting students' flow states and their construct through electroencephalogram: Reflective flow experiences, balance of challenge and skill, and sense of control. *Journal of Educational Computing Research, 58*(8), 1515-1540, Article 0735633120944084. https://doi.org/10.1177/0735633120944084

Yang, X. Z., Cheng, P. Y., Lin, L., Huang, Y. M., & Ren, Y. Q. (2019). Can an integrated system of electroencephalography and virtual reality further the understanding of relationships between attention, meditation, flow state, and creativity?. *Journal of Educational Computing Research, 57*(4), 846-876. https://doi.org/10.1177/0735633118770800

Yang, X. Z., Lin, L., Cheng, P. Y., Yang, X., Ren, Y. Q., & Huang, Y. M. (2018). Examining creativity through a virtual reality support system. *Etr&D-Educational Technology Research and Development, 66*(5), 1231-1254. https://doi.org/10.1007/s11423-018-9604-z

Yang, X. Z., Lin, L., Wen, Y., Cheng, P. Y., Yang, X., & An, Y. (2020). Time-compressed audio on attention, meditation, cognitive load, and learning. *Educational Technology & Society, 23*(3), 16-26. https://www.jstor.org/stable/26926423

Youdell, D., Lindley, M., Shapiro, K., Sun, Y., & Leng, Y. (2020). From science wars to transdisciplinarity: the inescapability of the neuroscience, biology and sociology of learning. *British Journal of Sociology of Education, 41*(6), 881-899. https://doi.org/10.1080/01425692.2020.1784709

Zhai, X. S., Fang, Q. S., Dong, Y., Wei, Z. H., Yuan, J., Cacciolatti, L., & Yang, Y. L. (2018). The effects of biofeedback-based stimulated recall on self-regulated online learning: A gender and cognitive taxonomy perspective. *Journal of Computer Assisted Learning, 34*(6), 775-786. https://doi.org/10.1111/jcal.12284

Referances of Table 2

Barraza, P., Dumas, G., Liu, H., Blanco-Gomez, G., van den Heuvel, M. I., Baart, M., & Pérez, A. (2019). Implementing EEG hyperscanning setups. *MethodsX, 6*, 428-436. https://doi.org/10.1016/j.mex.2019.02.021

Causa, M., La Paz, F., Radi, S., Oliver, J. P., Steinfeld, L., & Oreggioni, J. (2018, February). *A 64-channel wireless EEG recording system for wearable applications*. In 2018 IEEE 9th Latin American Symposium on Circuits & Systems (LASCAS), Puerto Vallarta, Mexico. https://ieeexplore.ieee.org/document/8399899

Chew, L. H., Teo, J., & Mountstephens, J. (2016). Aesthetic preference recognition of 3D shapes using EEG. *Cognitive Neurodynamics, 10*(2), 165-173. https://doi.org/10.1007/s11571-015-9363-z

Deuel, T. A., Pampin, J., Sundstrom, J., & Darvas, F. (2017). The Encephalophone: A novel musical biofeedback device using conscious control of electroencephalogram (EEG). *Frontiers in Human Neuroscience, 11*(213), 1-8. https://doi.org/10.3389/fnhum.2017.00213

Ekanayake, H. (2010). *P300 and Emotiv EPOC: Does Emotiv EPOC capture real EEG?* http://neurofeedback.visaduma.info/P300nEmotiv.pdf

Emotiv (2018). *EPOC Flex*. https://fccid.io/2ADIH-FLEX01/User-Manual/User-manual-4059138.pdf

Fiedler, P., Pedrosa, P., Griebel, S., Fonseca, C., Vaz, F., Supriyanto, E., F., Zanov, & Haueisen, J. (2015). Novel multipin electrode cap system for dry electroencephalography. *Brain topography, 28*(5), 647-656. https://doi.org/10.1007/s10548-015-0435-5

Guomundsdoottir, K. (2011). *Improving players' control over the NeuroSky brain-computer interface*. [Doctoral dissertation]. https://skemman.is/bitstream/1946/9187/1/ImprovingPlayersControlOverNeuroSkyBCI_ResearchReport_kristingud08.pdf

Ma, M. Y., & Wei, C. C. (2016). A comparative study of children's concentration performance on picture books: age, gender, and media forms. *Interactive Learning Environments, 24*(8), 1922-1937. https://doi.org/10.1080/10494820.2015.1060505

Mahajan, R., Majmudar, C. A., Khatun, S., Morshed, B. I., & Bidelman, G. M. (2014, October). *NeuroMonitor ambulatory EEG device: Comparative analysis and its application for cognitive load assessment*. In 2014 IEEE Healthcare Innovation Conference (HIC) (pp. 133-136), Seattle, WA, USA. https://doi.org/10.1109/HIC.2014.7038892

Sanchez-Cifo, M. A., Montero, F., & López, M. T. (2021). MuseStudio: Brain activity data management library for low-cost EEG devices. *Applied Sciences, 11*(16), 7644. https://doi.org/10.3390/app11167644

Soufineyestani, M., Dowling, D., & Khan, A. (2020). Electroencephalography (EEG) technology applications and available devices. *Applied Sciences, 10*(21), 7453. https://doi.org/10.3390/app10217453

Vourvopoulos, A., & Liarokapis, F. (2012, June). *Robot navigation using brain-computer interfaces*. In 2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications (pp. 1785-1792), Liverpool, UK. https://doi.org/10.1109/TrustCom.2012.247

Yoghourdjian, V., Yang, Y., Dwyer, T., Lawrence, L., Wybrow, M., & Marriott, K. (2020). Scalability of network visualisation from a cognitive load perspective. *IEEE Transactions on Visualization and Computer Graphics, 27*(2), 1677-1687. https://doi.org/10.48550/arXiv.2008.07944