Mapping Research Themes and Future Directions in Learning Style Detection Research: A Bibliometric and Content Analysis

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Abstract: This study aims to provide a comprehensive overview of the current state and potential future research in learning style detection. With the increasing number and diversity of research in this area, a quantitative approach is necessary to map out current themes and identify potential areas for future research. To achieve this goal, a bibliometric and content analysis will be conducted to map out the existing research and identify emerging topics and directions for future research. The study analyzes 1074 bibliographic sources from Scopus and visualizes the results of the bibliometric analysis through co-occurrence and thematic map analysis using VOSviewer and BibliometriX software. Content analysis is then conducted based on the results of the co-occurrence analysis. The findings reveal a significant increase in publications and citations in the field, with popular research topics including classification, adaptive learning, and MOOCs, and the most frequently used learning style models being Felder-Silverman, VARK, and Kolb. Emerging research topics include the use of EEG signals, online learning, and feature extraction. Future research may focus on classification, intelligent tutoring systems, MOOCs, online learning, adaptive learning, and deep learning. This study provides valuable insights into the current and future research trends in learning style detection, which can support the development of adaptive e-learning systems, intelligent tutoring systems, and MOOCs. By identifying popular research topics and emerging areas of study, this research can guide the design and implementation of effective online learning environments. Additionally, the study advances the field of e-learning knowledge by providing a comprehensive overview of the most frequently used learning style models and potential research areas. It sheds light on the ongoing development of learning style detection research and the potential for future advancements in the field, ultimately contributing to the growth and improvement of e-learning practices.

Keywords: Learning style detection, Bibliometric analysis, EEG, VOSviewer, BibliometriX

1. Introduction

Learning styles are a way to understand how different people approach learning (Goštautaitė and Sakalauskas, 2022) and how they prefer to receive and process information (Pashler et al., 2008). They are developed over time through long-term learning experiences (De Bello, 1990) and can influence an individual's learning preferences (Grey, Williams and Rebuschat, 2015). Understanding an individual's learning style can tailor learning strategies, content, and resources to their specific needs, leading to improved learning efficiency and engagement (Hmedna, El Mezouary and Baz, 2020). Hence, accurately identifying learners' learning styles is essential for personalized teaching and has significant research and practical value for implementing modern education methods (Li and Zhou, 2018).

Research on learning style detection has been increasing and is often related to classification based on learning style models. Currently, there are several learning style models being used, including Kolb, Felder-Silverman, VARK, and others. Felder-Silverman is the most commonly used model (Guabassi et al., 2019; Rasheed and Wahid, 2021a). There are two approaches to detecting learning styles: explicit recognition and implicit recognition (Zhang et al., 2021a). The explicit approach predominantly involves the administration of questionnaires to individuals for assessing their learning style preferences (Rajkumar and Ganapathy, 2020; Wouters and van der Meulen, 2020; Marosan et al., 2022). On the other hand, the implicit approach encompasses a diverse range of modalities, such as analyzing learning behavior patterns (Rasheed and Wahid, 2021b; Yousef et al., 2021), monitoring eye movements during learning tasks (Guabassi et al., 2019; Mu et al., 2019), utilizing facial image analysis (Gambo et al., 2018), and employing Electroencephalogram (EEG) technology to measure brain activity (Anoor et al., 2020; Zhang et al., 2021b). These methodologies are constantly developing and have been extensively embraced by researchers in the ever-changing field of learning style detection.

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As the research landscape on learning style detection continues to expand in terms of both quantity and diversity, there is a pressing need to comprehensively assess the current state of research in this field and identify potential avenues for future investigations. To achieve this, a quantitative approach, specifically bibliometric analysis, has been recognized as a suitable method (Ellegaard and Wallin, 2015; Kent Baker et al., 2020; Noman et al., 2022). However, despite its relevance and utility, the application of bibliometric analysis to study learning style detection has remained relatively scarce, prompting the necessity for more focused attention in this area.

The primary objective of our study is to employ a bibliometric analysis to meticulously map the existing themes and topics of research in learning style detection and discern the emergence of new research areas. Additionally, we aim to chart the future trajectory and potential directions for research in this domain. To achieve these objectives, we have formulated three specific research questions (RQs):

RQ1. What are the prevalent research themes and topics within the field of learning style detection?

RQ2. What novel research topics are currently emerging in the study of learning style detection?

RQ3. What is the future work and direction in the learning style detection study?

By addressing these RQs, our research endeavors to offer an explicit and comprehensive depiction of the current status and evolution of learning style detection research. Furthermore, through the integration of bibliometric analysis and content elaboration, we seek to identify potential areas for future research and provide valuable insights for researchers and practitioners in the field of learning style detection. The fusion of these methods allows for a more profound understanding of the existing body of knowledge and opens up avenues for further exploration in this vital area of study (Kent Baker et al., 2020).

2. Methods

2.1 Bibliography Data Collection

We decided to only use the Scopus database for our literature search because it is known to be the most comprehensive and to minimize variations in data and field tags that could occur if we used multiple databases. Additionally, the Scopus database has a larger number of publications and more citations (Zhu and Liu, 2020; Pranckutė, 2021), which we believe would provide sufficient data to understand the scientific landscape, research hotspots, and other relevant information (Zakaria et al., 2022). In this study, several steps were taken in data collection. Figure 1 shows the data collection steps from determining the topic to the bibliography data included in the bibliometric analysis.

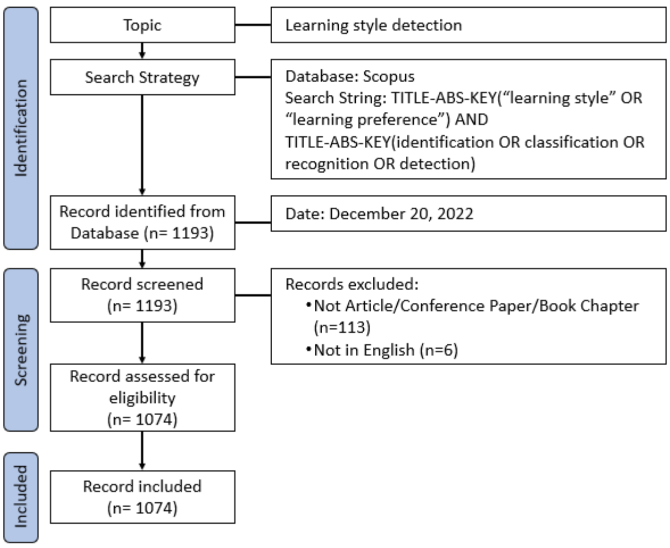

Figure 1: Search strategy adapted from the PRISMA flow diagram (Page et al., 2021)

As depicted in Figure 1, the data collection steps undertaken in this research follow and are adapted from the PRISMA flow diagram (Page et al., 2020). The data used is sourced from Scopus, which was obtained on December 20, 2022. The search terms used consist of two blocks, namely, related to the learning style and detection. This search is based on the title, keywords, and abstract containing both search terms. In terms of publication time, this research is only limited to the maximum year 2022. Other filters used are document type, which consists of journal articles, conference proceedings, and book chapters. In terms of language, data that is pulled is limited to papers written in English. Finally, a total of 1074 bibliography data was successfully pulled from Scopus, which was then processed using two applications, namely VOSviewer (van Eck and Waltman, 2021) and BibliometriX (Aria and Cuccurullo, 2017). All the software tools can be downloaded and used for free and are effective at conducting bibliometric analysis (Moral-Muñoz et al., 2020).

Bibliometric analysis often deals with vast amounts of data, frequently consisting of hundreds, if not thousands, of papers within a particular research field (Donthu et al., 2021). In such cases, the application of bibliometric analysis becomes relevant and justifiable due to the scale and complexity of the dataset. Notably, bibliometric analysis typically does not involve study selection and quality assessment steps as commonly seen in systematic reviews. Instead, the focus is primarily on selecting appropriate databases, designing an effective search strategy, and implementing relevant filters tailored to the research objectives (Zupic and Čater, 2015; Donthu et al., 2021). By following these guidelines, bibliometric analysis provides valuable insights into research trends, collaborations, and the impact of publications within a given field, making it a powerful and insightful tool in academic research.

2.2 Bibliometric and Content Analysis

In this study, bibliometric analysis is used to map out the current conditions and research mapping for the future (Ellegaard and Wallin, 2015; Li, Wu and Wu, 2017). Meanwhile, to elaborate and extract the future work and direction, a content analysis is carried out, which is a continuation of the cluster analysis obtained from the bibliometric analysis. Figure 2 shows the research structure used in this study. From Figure 2, three groups of analysis are carried out to answer the RQs. The descriptive analysis presents descriptive-quantitative results of the bibliography data, co-occurrence, and thematic map, are analysis of bibliometric analysis, and full-text review is a technique for content analysis. Bibliometric analysis has been shown to be an effective way of evaluating academic output and providing an objective reflection of a research topic (Haddad, 2017; Giménez-Espert and Prado-Gascó, 2019).

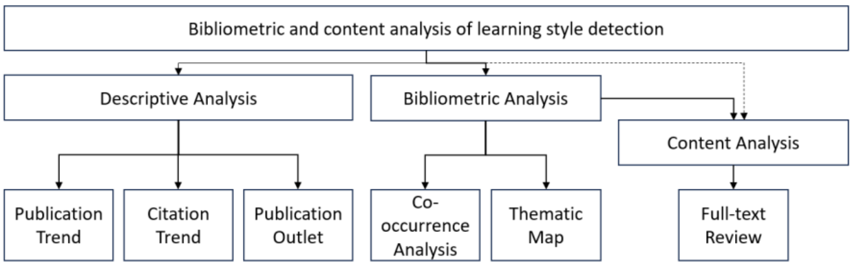

Figure 2: Research structure to answer RQs as adopted from (Kent Baker et al., 2020)

In the context of content analysis, Figure 2 serves as a crucial reference for selecting pertinent papers, guided by the co-occurrence analysis-derived mapping. This mapping provides a structured framework for identifying and retrieving full-text papers from each cluster, enabling a comprehensive investigation to address the third research question pertaining to the future direction of learning style detection research. The paper selection process is thoughtfully guided by trending and influential topics, considering key factors such as occurrence, average publication year, and citations as depicted in the VOSviewer output. A comprehensive account of the content analysis methodology employed can be found in Section 3.4.

3. Results and Discussion

In this research, bibliometric analysis is used to reveal the current state of research related to learning style detection. To start, descriptive results will be presented to provide a quantitative overview of the current state of research on learning style detection. Subsequently, the results of network analysis modelling produced from co-occurrence analysis and the thematic map will be presented to answer the research questions.

3.1 Descriptive Results

The publication chart over time is a valuable tool to assess the growth and prevalence of a specific research topic. Figure 3 depicts the progression of publications on learning style detection throughout the years. The research on this topic initiated in 1918, with no recorded publications until 1970. From 1970 onwards, it gradually gained momentum and steadily increased until the early 2000s. Notably, in 2006, there was a significant surge in publications, signalling a pivotal point in the field's development.

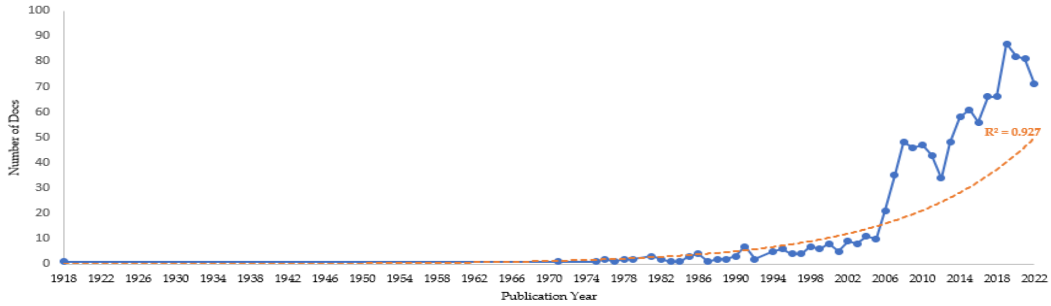

Figure 3: Publishing over time with a blue dotted-line represents the number of documents, while the orange dashed-line represents an exponential trend line

Furthermore, a trending line with an exponential trend was fitted to the data, yielding an impressive R-squared value of 0.927. This exponential trend line clearly illustrates the substantial and sustained interest in learning style detection research since 2006 until the present day. The remarkable increase in publications during this period indicates a persistent and noteworthy trend, underscoring the high level of attention and interest the topic has garnered within the academic community. The upsurge in publications on learning style detection from 2006 onwards reflects the growing significance and relevance of this area of study, paving the way for continued advancements and contributions to the field.

Aside from the publications chart over time, the number of citations per year chart is a significant measure of a research's popularity and impact on subsequent research. Figure 4 shows the number of citations chart from year to year. Along with the increase in publications in 2006, the number of citations also increased starting in 2006 and continued to rise in the following years. The increase in the number of citations follows a polynomial trend. In general, the number of citations increases in conjunction with the number of publications.

Additionally, it is important to consider information about the publication outlets related to learning style detection research. In this study, three types of documents were selected: journal articles, conference proceedings, and book chapters. Among these document types, journal articles were the most prevalent. Thus, the publication outlet graph presented in Figure 5 reflects this, with journals being the most common outlet. In Figure 5, in addition to showing the number of documents for each outlet, the average publication year is also represented by the colour bar. Where light green to yellow means a relatively young average publication year, and dark green means an older average publication year. From Figure 5, several journals can be seen as the choice for researchers.

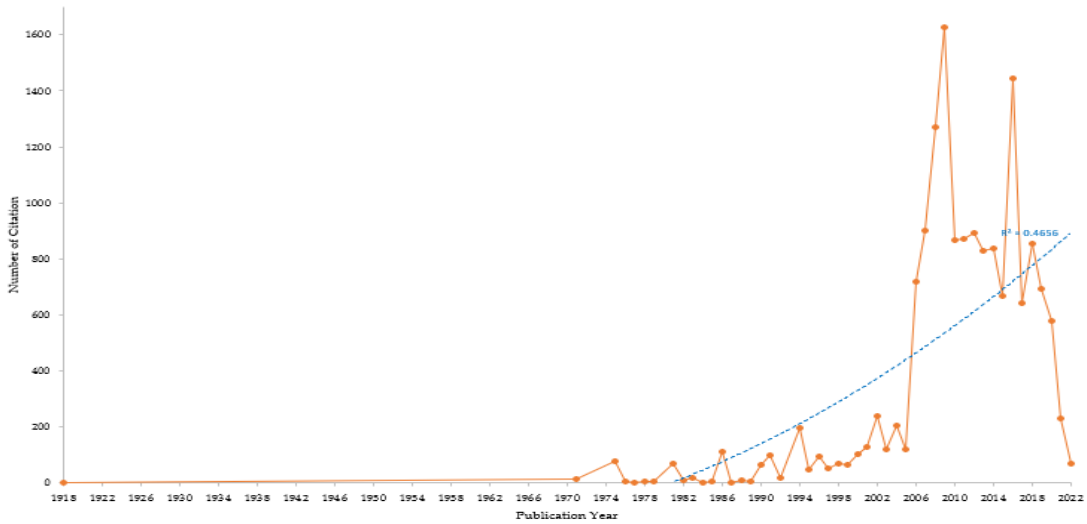

Figure 4: Citation over time with an orange dotted-line represents the number of citations, while the blue dashed-line represents a polynomial trend line

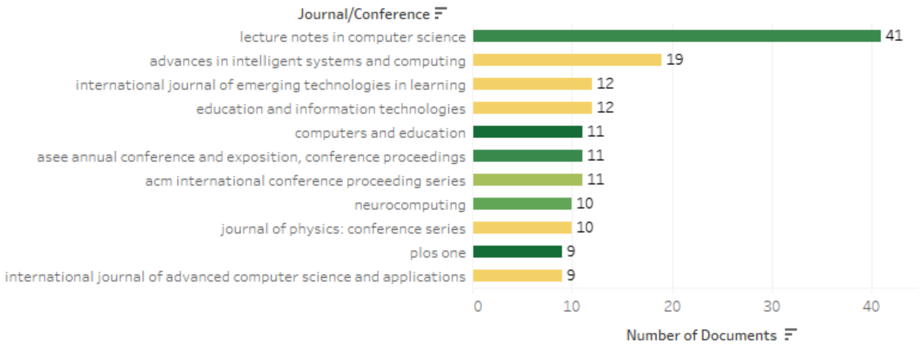

Figure 5: Top 11 Journal or Conference Proceedings that are outlets for publication

The data presented in Figure 5 illustrates the distribution of research publications in the field of learning style detection across various source types. Notably, Book Chapters in Lecture Notes in Computer Science garnered the highest number of papers, with 41 publications. Additionally, Journals such as Advances in Intelligent Systems and Computing, International Journal of Emerging Technology in Learning, Education and Information Technologies, and Computers and Education each contributed 19, 12, 12, and 11 papers, respectively. The ASEE Annual Conference and Exposition, along with the ACM International Conference Proceedings Series, contributed 11 publications each to the Conference Proceedings. Furthermore, the Journal Neurocomputing and Conference Proceedings in Journal of Physics: Conference Series both contained 10 papers. Lastly, PLOS One and International Journal of Advanced Computer Science and Applications accounted for 9 papers each. These insightful findings shed light on the diverse and prominent sources where learning style detection research is disseminated, providing valuable information for researchers and academicians in the field.

3.2 Main Research Themes and Topics

To answer RQ1 regarding the current state of research related to learning style detection, the visualization generated from VOSviewer can be used. The visualization from co-occurrence analysis maps how research topics are related, their popularity, and the clusters of topics that are created. Therefore, co-occurrence analysis can investigate the main themes and topics or crucial concepts of publications (Shafin et al., 2022). The co-occurrence analysis yields a network visualization in Figure 6, which reveals the presence of three distinct clusters of themes.

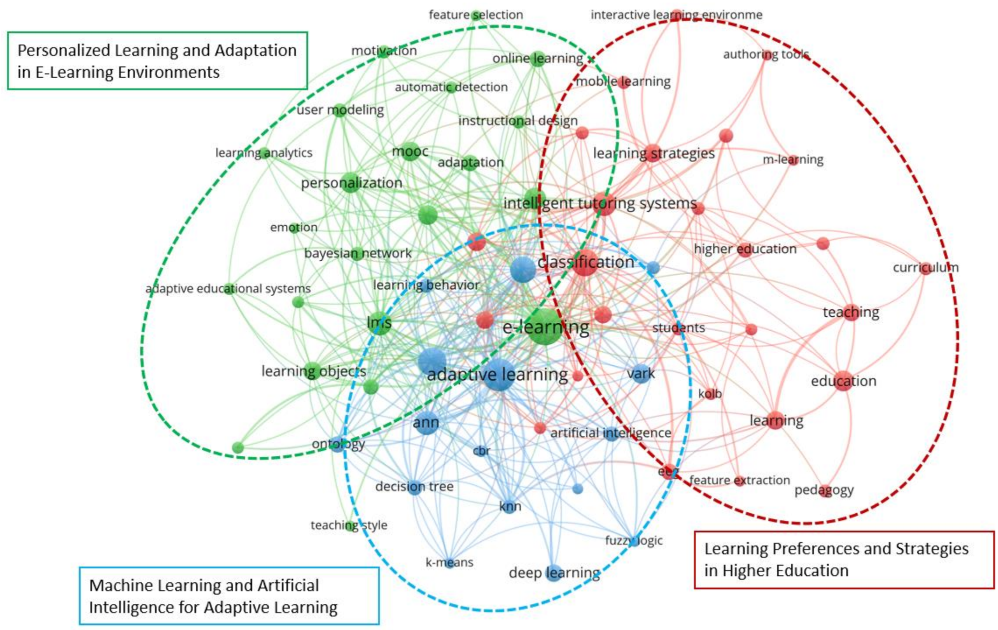

Figure 6: Network visualization from Co-occurrence analysis that results in 3 clusters

Each cluster is represented by a different color, with the red, green, and blue cluster corresponding to cluster 1, 2, and 3, respectively. The red cluster focuses on the learning preferences and strategies of higher education students using data mining and cluster analysis techniques. The green cluster's research theme is on personalized learning in e-learning environments using technologies such as educational data analysis and adaptive learning models. Meanwhile, the blue cluster deals with the use of the latest technologies such as machine learning, deep learning, and artificial intelligence to create adaptive learning environments, with the development of adaptive learning models and the identification of student learning styles accurately.

Cluster 1, represented by red, is focused on the research theme of learning preferences and strategies in higher education. Within this cluster, the most popular topics are classification and intelligent tutoring systems (Anoor et al., 2020; Mishra, Agarwal and Kolekar, 2021). These research topics aim to classify different learning styles using various modalities, such as mobile learning (Bunyakul, Wiwatwattana and Panjaburee, 2022) and blended learning (Shailaja and Sridaran, 2014), as well as intelligent tutoring systems. The research conducted using EEG signal modalities, as demonstrated by previous studies (Zhang et al., 2021c; 2021a), also falls into this cluster due to its close relation to the classification of learning styles. By exploring these topics, researchers can gain insight into the different strategies and preferences that students have for learning in higher education, which can help improve the effectiveness of teaching and learning.

Cluster 2, denoted by the color green, is dedicated to the research topic of personalized learning and adaptation in electronic learning environments. The cluster focuses on popular research topics of MOOCs and personalized learning. Studies within this cluster investigate the implementation of learning style detection on MOOCs platforms (Hmedna, El Mezouary and Baz, 2020; Rajkumar and Ganapathy, 2020) and efforts to personalize learning on the MOOC platform by considering student learning styles (Gambo and Shakir, 2021; Lin, Wang and Lan, 2022). This research is significant for enhancing the efficacy of e-learning environments by utilizing personalized learning to enhance students' efficiency and effectiveness in their learning process.

In cluster 3, denoted by the color blue, the research theme centers around machine learning and artificial intelligence in the context of adaptive learning. This cluster primarily focuses on adaptive learning approaches utilizing diverse machine learning algorithms, such as decision tree (Dutsinma and Temdee, 2020), k-means (Yusoff, Najib Bin Fathi and ., 2018), knn (Shekapure and Patil, 2019), and deep learning (Zhang et al., 2021c). These algorithms play a crucial role in analyzing student data and delivering personalized learning experiences tailored to the unique needs of individual learners. Leveraging machine learning and artificial intelligence techniques empowers researchers to enhance the effectiveness of adaptive learning, consequently facilitating more efficient attainment of students' learning objectives.

In addition, the field of education has conducted extensive research on learning style models such as Kolb, VARK, and Felder-Silverman. These models play a crucial role in identifying an individual's preferred learning method, and understanding these preferences can assist in developing effective teaching strategies. Figure 7 illustrates how these models are connected to various research topics, with Felder-Silverman being the most extensively researched (Zhang et al., 2021a). Machine learning plays a significant role in both VARK and Felder-Silverman, while Kolb has a lesser connection to it. However, all three models have ties to e-learning and classification research topics.

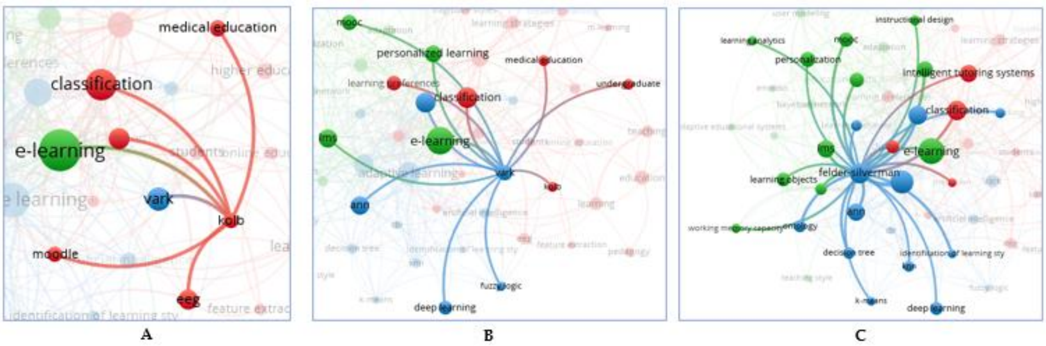

Figure 7: Three major learning style models (A=kolb, B=VARK, C=Felder-Silverman)

3.3 Emerging Topics

To answer RQ2 related to emerging topics in learning style detection research, the thematic map generated by BibliometriX can be used. This thematic map was first introduced by Cobo et al. (Cobo et al., 2011) using a strategic diagram approach with four quadrants. Each quadrant indicates a group of themes, namely motor theme, niche theme, emerging/declining theme, and basic theme in quadrants 1, 2, 3, and 4, respectively.

A strategic diagram in Figure 8 presents a thematic map of research topics related to learning style detection. Quadrant 3 shows which research topics are emerging or declining. The four topics in this quadrant are EEG, Kolb, online education, and feature extraction. However, it is not clear from this thematic map whether a research topic is emerging or declining. To confirm this, the output from a co-occurrence analysis using VOSviewer on an overlay visualization, shown in Figure 9, can be used. The overlay visualization displays the relationship between occurrence and publication year.

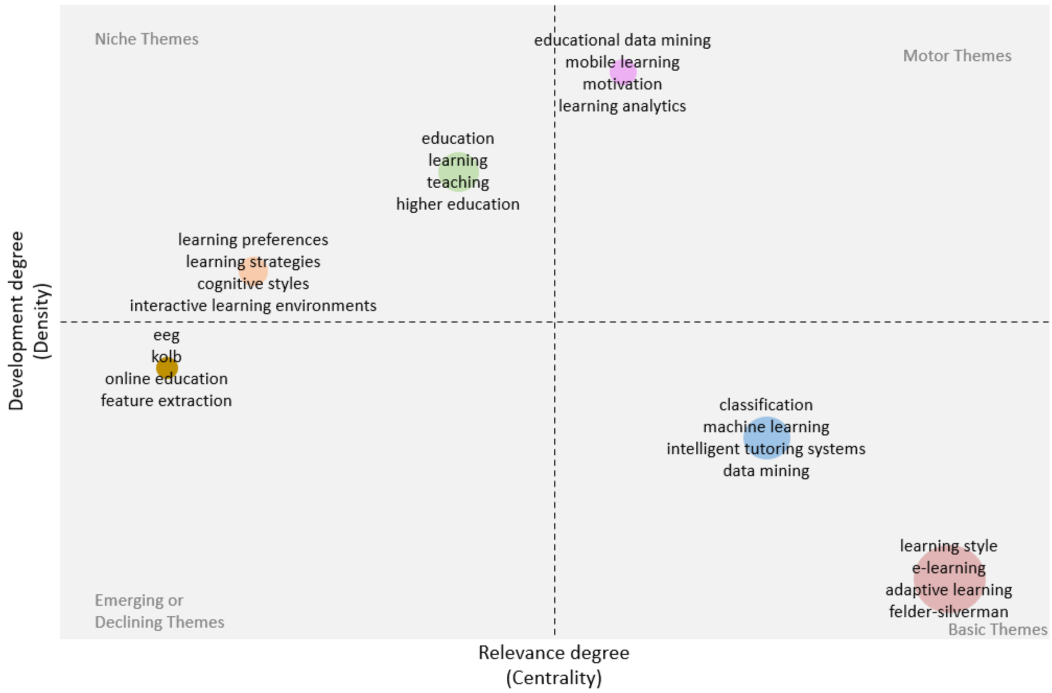

Figure 8: Strategic diagram presenting 4 quadrants with their respective labels

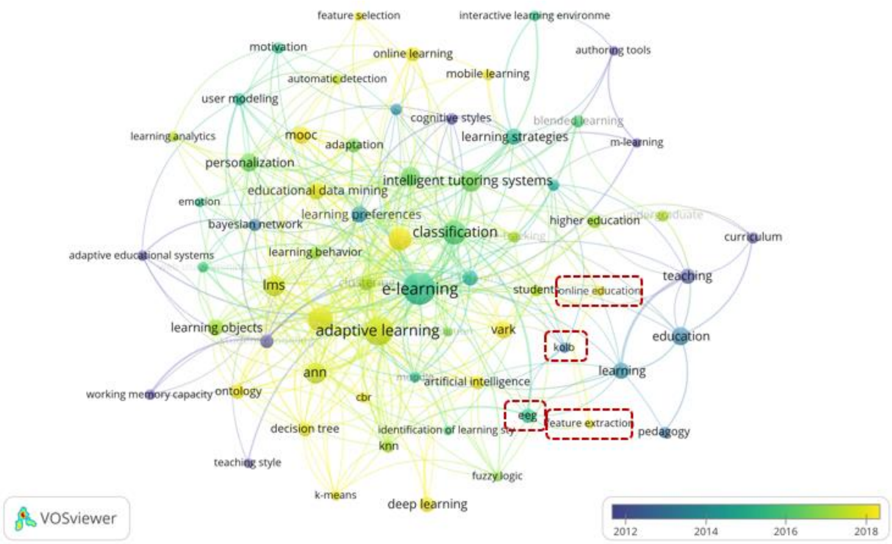

Figure 9: Overlay visualization between occurrence and average publication year with green to yellow indicating novel/emerging topics and the color blue indicating old/decreasing topics

Figure 9 shows the average publication year for each research topic through the colour of its node. Green to yellow signifies a novel publication year, while green to blue means an old publication year. Research topics with green to yellow node colours are considered emerging, while those with colours close to blue are considered declining. EEG, online learning, and feature extraction have green to yellow colours, indicating they are emerging topics. Kolb, on the other hand, has a colour close to blue, indicating it is a declining topic. To further support these findings, the number of publications and citations for each of these research topics can be mapped, as shown in Figure 10.

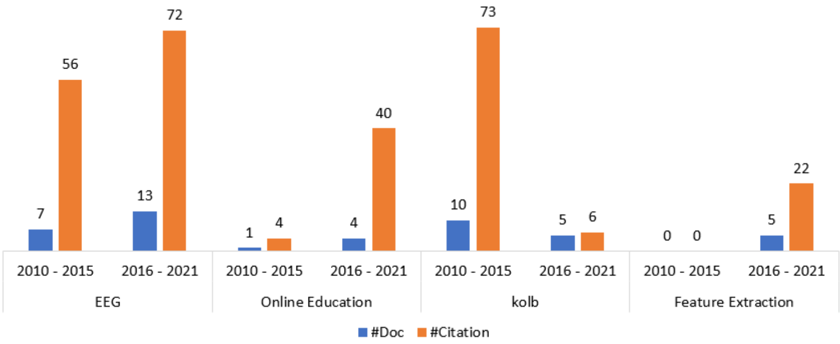

Figure 10: Chart of the number of documents (#Doc) and citations (#Citation) from the four topics in quadrant 3 to confirm whether these topics are emerging or declining from a comparison of two periods

Figure 10 shows the number of publications and citations for four research topics during two time periods: 2010-2015 and 2016-2021. These time periods were chosen to see if the number of publications and citations increased or decreased over a significant period. EEG, online learning, and feature extraction saw increases in both the number of publications and citations during the two time periods. Kolb, on the other hand, saw decreases in both the number of publications and citations. This aligns with the findings from the overlay visualization in Figure 9. As a result, it can be concluded that EEG, online learning, and feature extraction are emerging research topics in the field of learning style detection.

3.4 Future Works and Directions

In this study, a mapping of future work and direction was conducted to answer RQ3. To answer this RQ3, two analyses were conducted: a co-occurrence analysis with an overlay visualization and a content analysis. The overlay visualization will provide an overview of which research topics are currently developing and have a significant influence on learning style detection studies. Meanwhile, content analysis is used to explore potential future work. Figures 11 and 12 present the two overlay visualizations.

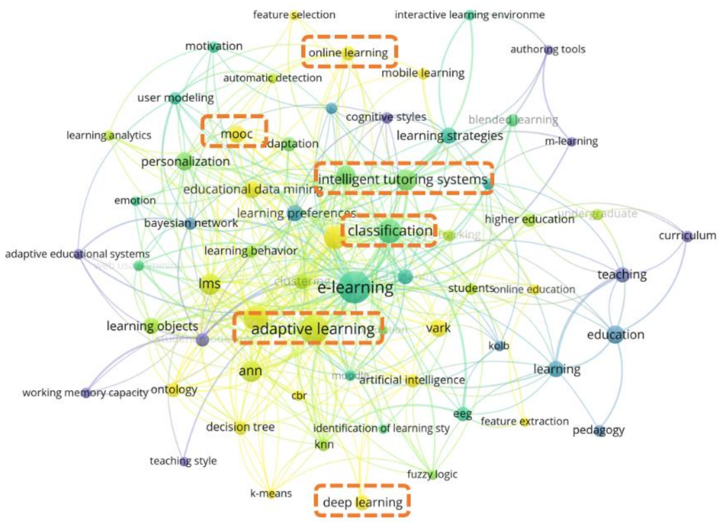

Figure 11: Overlay visualization for novel/old topics

Overlay visualizations based on publication time and the number of citations is presented in Figures 11 and 12. Based on the examination of these visualizations, six research themes that have garnered significant attention and citations in recent years are identified, namely classification, intelligent tutoring systems, MOOCs, online learning, adaptive learning, and deep learning. Given their popularity and influence in the field, these topics hold great potential for further exploration and serve as potential directions for future research.

Further investigation is required to address various issues related to the classification topic. Among these issues is the development of an e-learning system that is tailored to individual learning styles (Azzi et al., 2020). Furthermore, it is crucial to generalize the observed patterns of learning styles in diverse learners (Rasheed and Wahid, 2021a). To tackle these potential areas of future research, the classification results should be implemented in an e-learning system to enhance its adaptivity and tested with a larger sample size to enable generalization. Other potential areas of future work relate to intelligent tutoring systems, where personalized course elements based on predicted learning styles need to be developed (Mishra, Agarwal and Kolekar, 2021). Furthermore, there is a need for improved measures to monitor the accuracy of predicting learning styles in tutoring systems (Mishra, Agarwal and Kolekar, 2021). It is crucial to enhance the specificity of the tutoring system and improve the accuracy of evaluating learning style predictions.

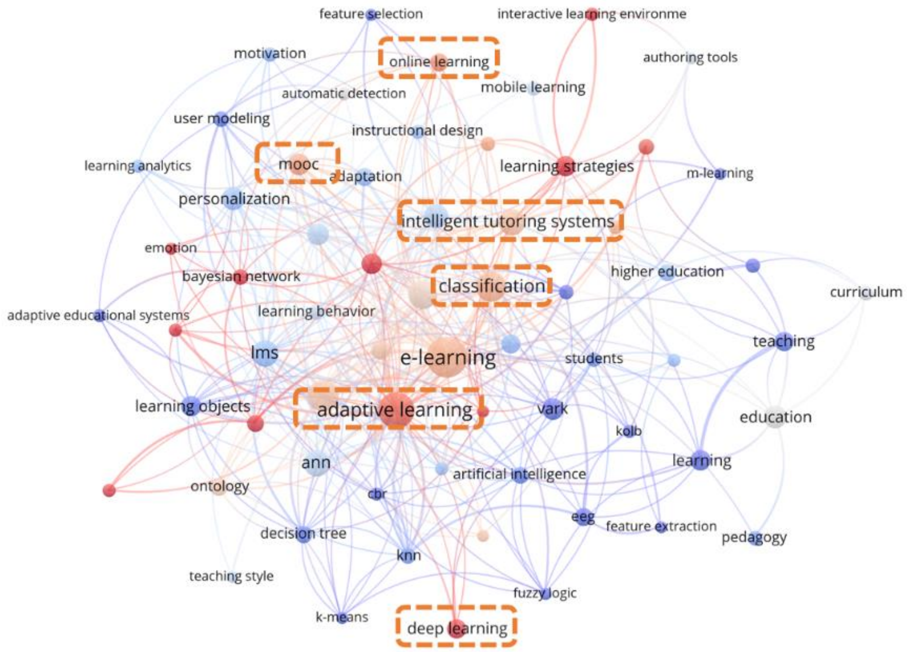

Figure 12: Overlay visualization for high/low citation

Numerous avenues for prospective investigation exist within the domain of MOOCs. One example is to the adoption of a learning analytics system, as discussed by Hmedna et al. (Hmedna, El Mezouary and Baz, 2020), which aims to enhance teachers' ability to enhance their students' academic outcomes. There is a pressing need for extensive study on MOOCs (Rajkumar and Ganapathy, 2020). Additionally, it is crucial to investigate novel approaches to enhance the precision of identifying pedagogical strategies that prove effective in the context of online learning (Li and Zhou, 2018). In order to delve deeper into the subject matter of online learning, it is important to conduct supplementary experiments involving students and their experiences inside a controlled laboratory environment (Yousef et al., 2021). It is also advisable to create instructional videos to provide a better understanding of online learning for students (Mu et al., 2019).

Adaptive learning presents potential avenues for future research, influencing the trajectory of forthcoming studies on learning style detection. A deeper exploration of learning behaviors is imperative to enhance accuracy and gain comprehensive insights into diverse learning styles (Zhang et al., 2020). Furthermore, further research is warranted concerning students' characteristics, encompassing their learning objectives, knowledge, and motivation, to facilitate a more profound comprehension and refinement of detection precision (Marosan et al., 2022). Additionally, continual investigations into the learning environment remain crucial (Wouters and van der Meulen, 2020).

In summary, the potential for future work in the field of learning style detection includes further design and implementation of adaptive e-learning systems, personalization of course elements based on learning style predictions, better metrics for evaluating learning style predictions in tutoring systems, implementation of analytics systems for MOOCs, more experimentation and instructional videos for online learning, investigation of learning behaviors and student characteristics in adaptive learning, and exploration of deep learning techniques (Gambo et al., 2018) and EEG-based datasets for detection (Zhang et al., 2021c).

The findings of this study hold significant practical implications for the advancement of e-learning. Through the identification of popular research topics and emerging areas in learning style detection, this research can offer valuable guidance for the design and implementation of adaptive e-learning systems, intelligent tutoring systems, and MOOCs. By incorporating frequently utilized learning style models like Felder-Silverman, VARK, and Kolb, e-learning designers can tailor course elements to match individual learning style predictions, thereby enhancing personalization. Additionally, the study emphasizes the importance of ongoing exploration of the learning environment and a deeper investigation into student characteristics to enhance the accuracy of learning style detection. The potential for future research in learning style detection, such as the exploration of deep learning techniques and EEG-based datasets for detection, can advance e-learning development and lead to more effective online learning environments. Therefore, the implications of this study have practical significance for e-learning practitioners and developers.

4. Conclusion

This study employed a rigorous bibliometric analysis to comprehensively map and evaluate the current state of learning style detection research. Additionally, a content analysis, guided by the insights from the bibliometric analysis, was undertaken to discern future research directions and avenues for exploration. Through co-occurrence analysis and thematic map analysis, the study successfully elucidated various research topics currently under development, encompassing areas such as classification, intelligent tutoring systems, MOOCs, online learning, adaptive learning, and deep learning. Furthermore, emerging research topics, exemplified by the utilization of EEG signals for classification purposes, were also identified, indicating the evolving nature of the field.

While learning style research has witnessed continuous development over time, several potential research directions warrant attention in the future. Firstly, the need for broader generalization necessitates an increase in the number of respondents and the utilization of diverse methodologies to ensure robust findings. Secondly, there is a pressing demand to enhance the accuracy of detection models, both from methodological and algorithmic perspectives, to yield more reliable and precise outcomes. In addition, using EEG signals to determine learning styles has shown promise due to the wide range of tasks for which EEG may be applied in many areas.

In conclusion, this study has shed light on the current landscape of learning style detection research while providing valuable insights into promising areas for future exploration. By continuing to address these research gaps and advancing methodological approaches, researchers can contribute to the ongoing growth and significance of learning style detection research, ultimately fostering more effective and personalized learning experiences for diverse learners (Narudin, Nasir and Fuad, 2021).

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