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Research Trends on the Multiple Representation Learning Model, A Systematic Review (2016-2025)

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ABSTRACT

This study aims to identify and analyze research trends on multi-representational learning models in science education during the period 2016-2025 through a systematic review approach. Data were collected from the Dimensions.ai and Google Scholar databases, then analyzed using PoP and VOSviewer software to reveal publication patterns, types of publications, and collaboration networks between researchers. The results show a significant increase in the number of publications, dominated by journal articles, followed by conference proceedings and research reports. Bibliometric analysis reveals increasingly close collaboration networks, especially in Asia and Europe, which strengthen the development of multi-representational learning theories and practices. The main research topics include the effectiveness of models in improving understanding of science concepts, technology integration, and the development of multi-representational-based learning media. These findings emphasize the important role of multi-representational learning models in improving the quality of science learning through various forms of visual, verbal, and symbolic representations. This study provides a strong foundation for the development of innovative and adaptive learning practices and recommends further research in various contexts and levels of education.

INTRODUCTION

In the realm of science education, especially in physics and chemistry subjects, students face quite complex challenges. Abstract and conceptual materials require high-level thinking skills, where students do not only memorize definitions and formulas, but must also be able to integrate various forms of representation to solve scientific problems. Microscopic concepts that cannot be observed directly, such as field forces, subatomic particles, chemical bonds, and molecular interactions, often make it difficult for students to form a complete and comprehensive mental picture.

Therefore, a learning approach is needed that does not only emphasize memorization, but also encourages active construction of meaning through various cognitive representation pathways. One approach that has proven effective in overcoming this problem is the multi-representation-based learning model. This model refers to a pedagogical strategy that presents information in various forms of representation, such as verbal (text descriptions), visual (pictures, diagrams, molecular models), symbolic (mathematical equations or chemical reactions), and graphs (relationships between variables). With this approach, students can develop the ability to connect and integrate various representations in understanding scientific concepts more deeply.

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For example, in physics, motion phenomena can be explained through position-time graphs, kinematic equations, and verbal descriptions. Meanwhile, in chemistry, the concept of exothermic reactions can be understood through reaction equations, energy diagrams, and particle models. The ability to move and integrate between these representations is a crucial aspect in improving students' conceptual understanding and problem-solving skills.

Various studies support the effectiveness of the multi-representation approach in science learning. Marpaung and Simanjuntak (2018) found that the integration of multi-representations in physics learning can improve learning outcomes while developing students' critical thinking skills. The findings of Rahmat et al. (2019) also show that the simultaneous presentation of physics concepts through various representations strengthens students' understanding, especially on abstract topics such as vibrations and waves. In chemistry learning, molecular representations such as the ball-and-peg model, orbital diagrams, and Lewis notation have been shown to help students understand atomic structure, chemical bonds, and reactions. Conversely, learning that relies only on one form of representation often leads to misconceptions, while the integration of multi-representations can reduce ambiguity and strengthen cognitive elaboration.

Research by Doyan et al. (2018) emphasized that the multi-representation approach not only improves conceptual understanding but also problem-solving skills. In physics, students who are accustomed to using multiple representations are better able to choose the right solution strategy according to the characteristics of the problem. In chemistry, the ability to connect experimental data, reaction result graphs, and stoichiometric equations is very important in answering quantitative and predictive questions. This shows that representational skills play an important role in mastering scientific content and processes in both subjects.

Furthermore, Amiroh et al. (2021) in their study at the higher education level found that students who took part in multi-representation-based learning showed better conceptual mastery, both on the topic of waves in physics and thermochemistry in chemistry. They were able to integrate various forms of information to explain scientific phenomena logically and systematically. This finding strengthens the argument that the multi-representation approach is universal and can be applied effectively at various levels of education and across subjects.

The success of implementing this learning model is highly dependent on the consistency and interconnectedness between representations. Kurniasari and Wasis (2021) stated that students' skills in connecting and transforming information between representations are positively correlated with the depth of their conceptual understanding. In practice, teachers need to ensure that each representation used supports each other to explain the same concept from various perspectives. For example, in explaining reaction enthalpy in chemistry, teachers can present energy change graphs, thermochemical equations, and visual simulations of heat transfer. Meanwhile, in physics, the concepts of work and energy can be reinforced through force-displacement graphs, mathematical formulas, and narrative analysis of physical events.

Optimal implementation of the multi-representation approach requires the active role of teachers as learning facilitators. Teachers must have pedagogical skills and a deep understanding of the material in order to choose the most appropriate and complementary types of representation. Hasbullah et al. (2019) emphasized the importance of learning planning involving interactive media such as digital simulations, experimental videos, and representative worksheets that allow students to actively move between representations. Learning activities also need to be designed to encourage discussion, exploration, and reflection on the interrelationships of the representations used. In line with the demands of the Independent Curriculum and the development of 21st-century competencies, the multi-representation-based learning model is a strategic alternative that needs to be systematically integrated into science learning, especially physics and chemistry. This approach supports the strengthening of scientific literacy, critical thinking skills, and mastery of information technology which are integral parts of the Pancasila student profile.

Therefore, the implementation of multi-representation is not only relevant to improving academic achievement, but also forming a generation of learners who are adaptive, creative, and able to think across disciplines. Thus, it can be concluded that the multi-representation-based learning approach makes a significant contribution to improving the quality of physics and chemistry learning. This approach facilitates students in building a complete conceptual understanding, developing critical thinking and problem-solving skills, and forming a systematic scientific mindset. Through the integration of verbal, visual, graphic, and symbolic representations, students can explore science concepts comprehensively and meaningfully. Therefore, it is important for educators and education policy makers to encourage the wider application of this approach in the science teaching and learning process at various levels of education.

METHODS

This study uses a descriptive analysis method that aims to identify and describe research trends related to multi-representation learning models. This method allows researchers to obtain a clear and systematic picture of research developments in the field by processing relevant data quantitatively and qualitatively.

The data used in this study came from Google Scholar, which is known to have strict document selection standards that guarantee the quality and relevance of the documents analyzed. The range of data collected includes documents published between 2016 and 2025, with a total of 2,825,002 documents. To process the data, researchers used several analytical tools, namely Publish or Perish (PoP) to collect and process bibliometric data, Dimension.ai as a supporting tool to enrich the analysis of citation networks and research trends, and VOSviewer which is used to visualize networks, overlays, and keyword distribution densities that focus on multi-representation learning models.

The analytical approach applied in this study consists of two main methods. First, quantitative analysis using VOSviewer software to graphically visualize bibliometric data, making it easier to identify patterns, clusters, and relationships between relevant keywords or documents. Second, qualitative analysis is conducted through content analysis to provide an in-depth interpretation of the meaning and context of emerging research trends. The combination of these two approaches allows the study to provide a holistic picture of the development and direction of research in multi-representational learning models, while identifying potential areas for further development.

RESULTS AND DISCUSSION

This study aims to describe research trends related to multi-representational learning models during the period 2016 to 2025. The analysis was conducted by examining the publication keyword trend graph, dominant publication types, top ten sources, and ten main trends of researchers in this field. The trend data was obtained and analyzed using the Dimensions.ai platform. In addition, data taken from Google Scholar and processed through PoP (Publish or Perish) was further analyzed using VosViewer software. This analysis includes three main aspects, namely network visualization, overlay visualization, and density visualization.

The multi-representation learning model is an innovative approach in education that integrates various forms of representation simultaneously to deepen students' understanding of scientific concepts. This approach utilizes verbal, mathematical, visual, graphic, physical, and symbolic representations, each of which has an important role in conveying information comprehensively. This is based on the understanding that complex scientific phenomena cannot be fully explained with just one type of representation (Gilbert, 2010). For example, in physics and chemistry learning, concepts such as force, energy, and molecular structure become easier to understand when presented through a combination of formulas, images, graphs, and concrete models. The theoretical basis of this model comes from a cognitive perspective that emphasizes that the learning process will be more effective if information is delivered through various complementary methods. Duit and Treagust (2012) emphasize that representation plays an important role in science learning because it helps overcome the limitations of abstract thinking, especially in explaining phenomena that cannot be seen directly. Thus, the use of various representations serves as a bridge between the real world and students' conceptual understanding, while strengthening the connections between the concepts learned, thereby increasing long-term memory and the ability to transfer knowledge.

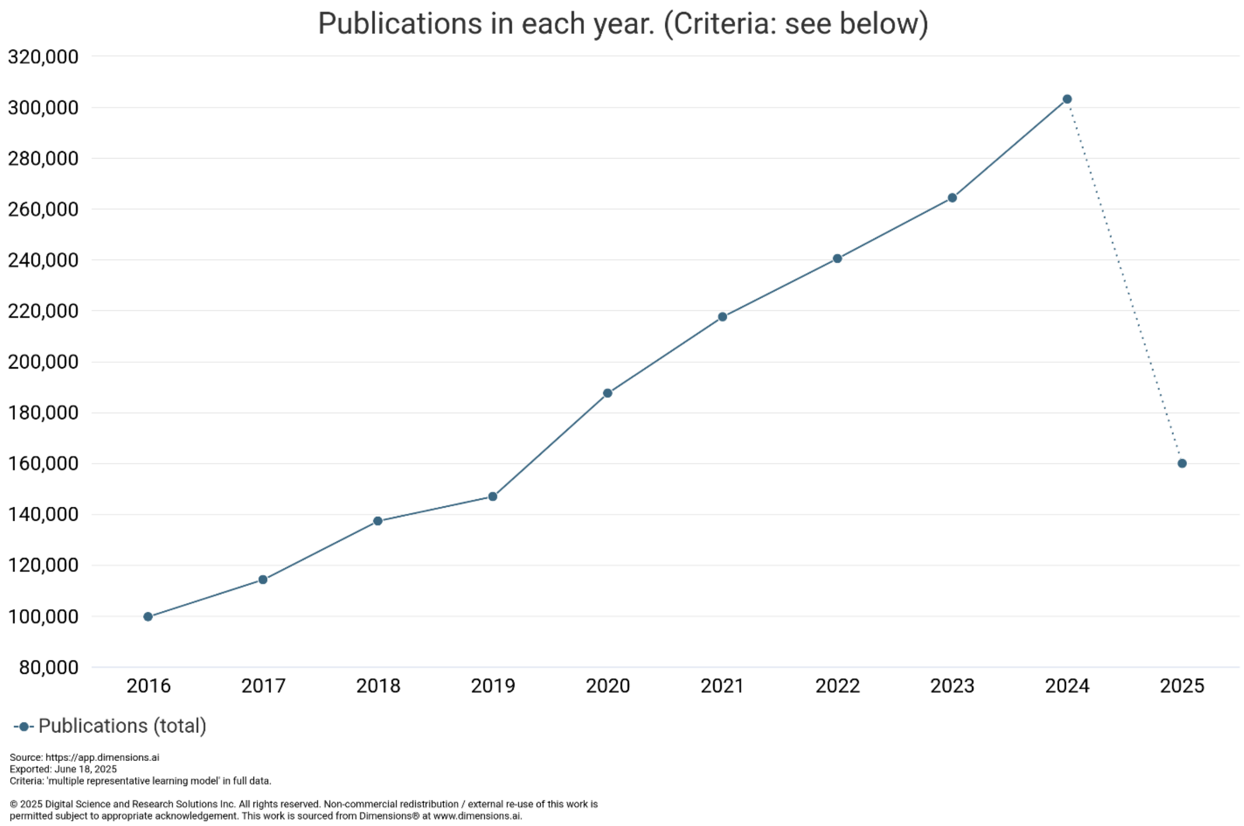

Figure 1. Research Trends in Multiple Representation Learning Model

Publication data related to multi-representation learning models from 2016 to 2025 shows a consistent and significant growth trend (Figure 1). In 2016, the number of publications was recorded at 99,701, then gradually increased each year to 114,265 in

2017, 137,302 in 2018, and 146,925 in 2019. A sharper spike occurred starting in 2020 with 187,557 publications, which continued to increase to 217,557 in 2021, 240,484 in 2022, and 264,354 in 2023. The highest peak was reached in 2024 with a total of 303,131 publications, indicating the peak of interest and research activity in this field during that period. However, in 2025 there is a significant projected decrease in the number of publications to 159,930, which is most likely due to incomplete data because the year is still ongoing or changes in the data collection methodology. Overall, the cumulative total of publications during this period reached 2,825,002, indicating the great attention and development of research in multi-representation learning models. This trend reflects the dynamics of research that continues to grow with peak activity in 2024, while also indicating the need for further monitoring of the 2025 data to understand whether the decline is a temporary phenomenon or the beginning of a long-term trend change.

Table 1. Trends in Multiple Representation Based on Publication Types

Publication Type	Publications
Article	1,589,620
Chapter	477,818
Preprint	236,657
Edited Book	201,689
Monograph	173,858
Proceeding	145,360

This table (Table 1) illustrates the distribution of publication types in multiple representation learning model research during the observed period. Scientific articles dominate with 1,589,620 publications, confirming that journal articles are the main media for disseminating research results in this field, which usually go through a strict peer-review process and therefore have high credibility. Book chapters are in second place with 477,818 publications, indicating the important role of books as a means of compiling more in-depth and structured research, often used to present comprehensive literature or theory reviews. Preprints with 236,657 publications show a significant trend in the rapid and open dissemination of knowledge before the formal peer-review process, which is very important in a rapidly developing field such as multiple representation learning. Edited books with 201,689 publications contribute to academic discourse by collecting various articles from different authors on a particular theme. Monographs, numbering 173,858, are usually in-depth research works that focus on a specific topic, indicating highly focused and detailed research. Finally, conference proceedings with 145,360 publications demonstrate the importance of scientific forums as a place for direct exchange of ideas and latest research results, which are also important media in this research community. Overall, this distribution reflects the diversity of publication media used to disseminate knowledge and research developments in multiple representation learning models.

Table 2. Top 10 Sources Title Trend of Multiple Representation Learning Model in 2016-2025

Name	Publications	Citations	Citations Mean
arXiv	140,067	73,500	0.52
SSRN Electronic Journal	40,669	234,970	5.78
Lecture Notes in Computer Science	36,706	499,161	13.60
bioRxiv	31,581	95,711	3.03
IEEE Access	14,111	305,008	21.61
PLOS ONE	13,516	425,228	31,46
Research Square	11,616	8,202	0.71
Scientific Reports	11,573	247,589	21.39
Sustainability	10,606	182,841	17.24
Behavioral and Brain Sciences	10,358	233,582	22.55

This table (Table 2) displays the top ten publication sources that are the main media for disseminating research in the field of multiple representation learning models, complete with the number of publications, total citations, and average citations per publication (citations mean). arXiv is the source with the largest number of publications, reaching 140,067 articles. However, its average citation is relatively low (0.52), which reflects the characteristics of arXiv as a preprint repository that provides fast and broad access, but not necessarily all works have been peer-reviewed or received high citations. SSRN Electronic Journal, although it has a smaller number of publications (40,669), shows quite a large influence with a total of citations reaching 234,970 and an average citation of 5.78, indicating the quality and relevance of research in this field is quite high. Lecture Notes in Computer Science occupies an important position with 36,706 publications and a very high total citation of 499,161, and an average citation of 13.60. This indicates that publications in this series are highly regarded and frequently cited in the academic community, especially in computer science and technology. bioRxiv as a preprint repository in biology also contributed significantly with 31,581 publications and an average citation of 3.03, indicating a growing interest in the application of multiple representation learning in life sciences. IEEE Access and PLOS ONE showed very strong academic impact with average citations of 21.61 and 31.46, respectively, although their number of publications is smaller than arXiv. This indicates that articles published in these journals are of high quality and are frequently cited. Research Square had a relatively large number of publications (11,616) but with low total citations and average citations (0.71), which may reflect its status as a relatively new preprint platform or the lack of rigorous peer-review. Scientific Reports, Sustainability, and Behavioral and Brain Sciences also show significant impact with high average citations (21.39, 17.24, and 22.55), indicating that publications in these journals are highly regarded and contribute significantly to the development of science in the field of multiple representation learning. The distribution of publications and citations in this table indicates that although preprint repositories such as arXiv and bioRxiv provide large publication volumes and fast access, peer-reviewed journals and publication series such as IEEE Access, PLOS ONE, and Lecture Notes in Computer Science have a higher academic impact based on average citations. This emphasizes the importance of publication quality and credibility in building scientific influence in the field of multiple representation learning models.

The multiple representation learning model, as developed in the SiMaYang model, aims to improve students' representational abilities by encouraging them to move and connect various forms of scientific phenomenon representation. This model emphasizes the importance of interaction between macroscopic, submicroscopic, and symbolic levels in building a solid mental model (Sunyono, 2015). Representational competence is the main indicator of learning success, where students who are able to interpret and compare various representations can explain scientific phenomena more holistically and deeply (Eilam & Gilbert, 2014). Several theories support the development of this model, including constructivism theory which emphasizes learning as an active process of building knowledge based on experience (Piaget, 1976), information processing theory which explains how students manage information from various representations (Merrill, 2002), and dual coding theory which states that presenting information in verbal and visual formats simultaneously facilitates understanding (Paivio, 1986). Ainsworth (2006) added that multiple representations have three main functions: complementation, construction, and comparison, which together improve the quality of science learning. The success of this model is highly dependent on the ability of learners to move and connect representations flexibly, known as representational fluency (Eilam & Gilbert, 2014).

Table 3. Top 10 Trends of Researchers Researching Multiple Representation Learning Model in 2016-2025

Name Organization, Country	**Publications**	**Citations**	**Citations Mean**
Roger J R Levesque Indiana University Bloomington, United States	767	795	1.04
Dacheng Tao Nanyang Technological University, Singapore	680	45,647	67.13
Saul I Gass University of Maryland, College Park, United State	568	2,712	4.77
Licheng C Jiao Xidian University, China	475	14,458	30.44
Heinz Mehlhorn Heinrich Heine University Düsseldorf, Germany	466	98	0.21
Xuelong Li Northwestern Polytechnical University, China	466	25,460	54.64
Witold Pedrycz University of Alberta, Canada	436	16,661	38.21
Dinggang G Shen ShanghaiTech University, China	429	25,457	59.34
Tat-Sheng Chua National University of Singapore, Singapore	408	17,944	43.98
Phillip S Yu University of Illinois at Chicago, United States	399	38,893	97.48

Table 3 lists the top ten researchers who have made significant contributions to research on multiple representation learning models during the period 2016 to 2025, complete with the number of publications, total citations, and average citations per publication. Roger J R Levesque from Indiana University Bloomington, USA, leads with 767 publications and 795 total citations, although his average citation is relatively low (1.04), indicating high productivity but moderate citation impact. In contrast, Dacheng Tao from Nanyang Technological University, Singapore, despite having a slightly lower number of publications (680), shows a very large academic impact with a total of 45,647 citations and an average citation of 67.13, indicating high research quality and relevance. Other researchers such as Saul I Gass (University of Maryland), Licheng C Jiao (Xidian University), and Xuelong Li (Northwestern Polytechnical University) also show significant contributions with a substantial number of publications and high average citations, reflecting strong academic recognition. Several researchers from institutions in China, such as Dinggang G Shen and Licheng C Jiao, show a strong trend of increasing research in the region, with high citation rates as well, indicating globally competitive research quality. Meanwhile, researchers from countries such as Germany, Canada, and Singapore have also enriched the research landscape, demonstrating the multidisciplinary and international nature of the field of multiple representation learning. Overall, these data indicate that while the number of publications is an indicator of productivity, the quality and impact of research as measured by citation rates are also very important in assessing the scientific contributions of leading researchers in the field.

The application of the multi-representation learning model provides various significant benefits in the learning process, such as improving conceptual understanding, reducing misconceptions, and increasing students' motivation and interest in learning. This approach also strengthens problem-solving skills by training students to translate information between different representations, and supports differentiated learning according to each individual's learning style. Thus, this model not only enriches the learning experience but also improves the quality of scientific understanding as a whole.

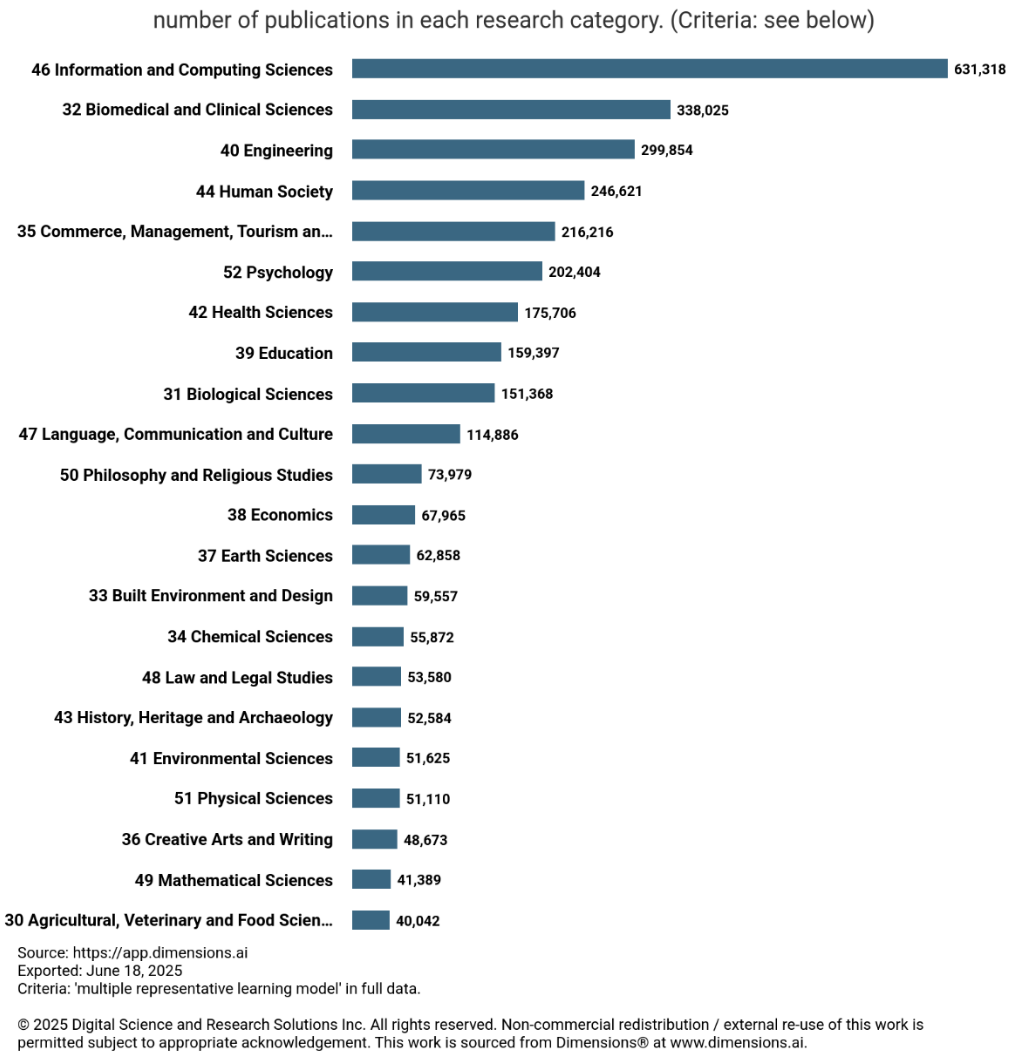

Figure 2. Research categories based on the classification of Fields of Research (ANZSRC 2020)

This chart shows the distribution of the number of scientific publications by research category according to the 2020 ANZSRC classification, or the 2020 Australian and New Zealand Standard Research Classification (a standard classification system used to measure and analyze research and development (R&D) activities in Australia and New Zealand), with search criteria related to the multi-representation learning model. It can be seen that the Information and Computing Sciences category dominates with the highest number of publications reaching 631,318, indicating a very large research focus on computer science and information technology in the context of this learning model. Followed by Biomedical and Clinical Sciences with 338,025 publications and Engineering with 299,854 publications, indicating that the health and engineering fields are also significant research areas. Other categories such as Human Society (246,621), Commerce, Management, Tourism (216,216), and Psychology (202,404) show extensive multidisciplinary involvement, reflecting the application of the multi-representation learning model in various social and behavioral fields. On the other hand, the category with the fewest publications is Agricultural, Veterinary and Food Sciences with 40,042 publications, indicating that this field is still relatively under-explored in the context of this learning model. Overall, this data shows a significant imbalance in the distribution of research, with a strong concentration in technology and health, while other fields such as creative arts, mathematics, and environmental sciences have smaller but still relevant contributions. This reflects the research trend that is heavily focused on the development of technology and its applications in health sciences and engineering, while also opening up opportunities for further exploration in other fields.

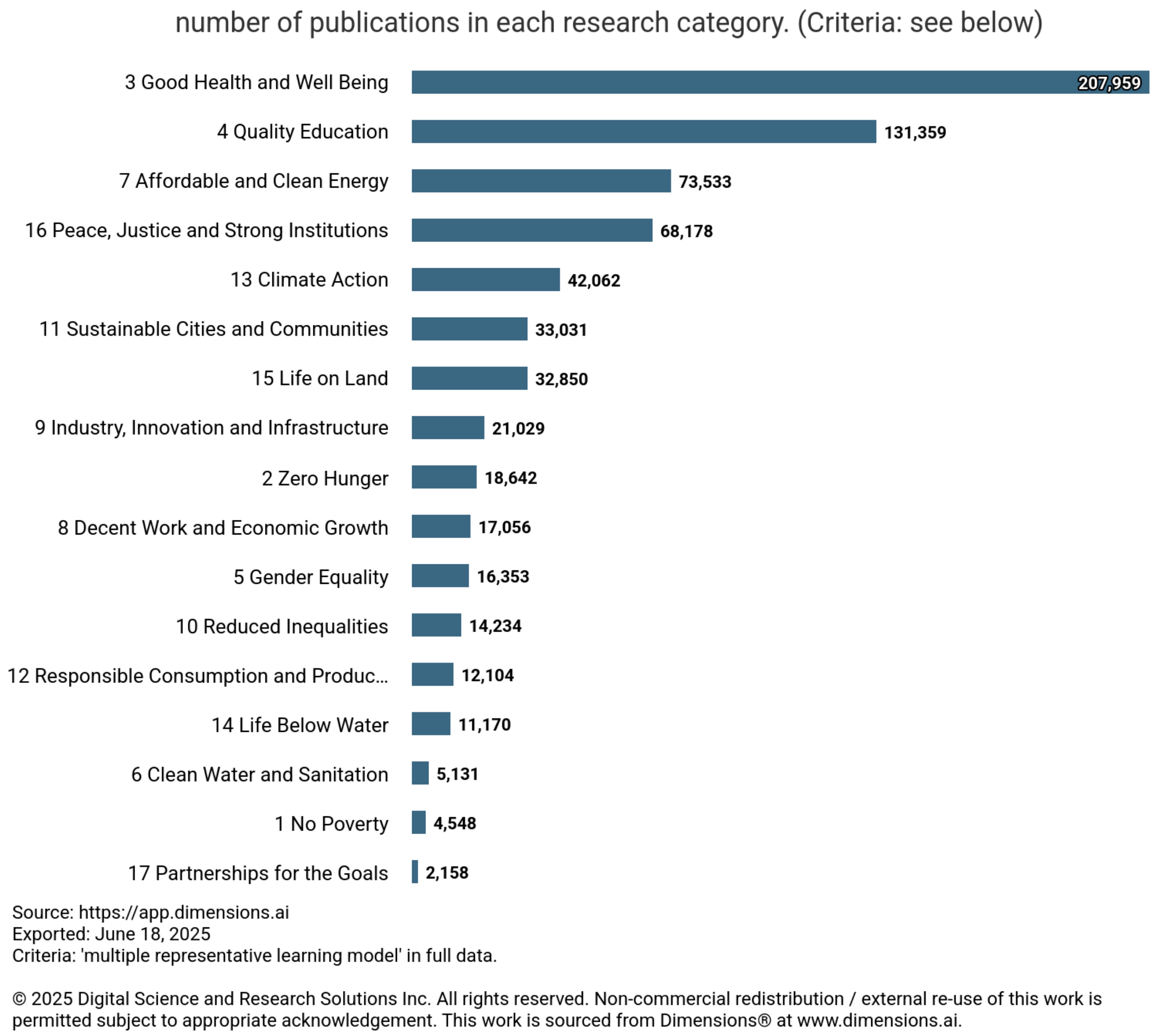

Figure 3. Research categories based on the classification of Sustainable Development Goals (SDGs)

This chart illustrates the distribution of the number of scientific publications related to the multiple representation learning model based on the Sustainable Development Goals (SDGs) classification from 2016 to 2025. It can be seen that the Good Health and Well Being category dominates with the highest number of publications reaching 207,959, indicating a very large research focus on the health and well-being aspects in the context of this learning model. Followed by Quality Education with 131,359 publications, confirming the importance of quality education as one of the main objectives in this study. Categories such as Affordable and Clean Energy (73,533) and Peace, Justice and Strong Institutions (68,178) also show significant attention, reflecting the relevance of research to broader social and environmental issues. However, there is a quite striking disparity, where several goals such as No Poverty (4,548), Clean Water and Sanitation (5,131), and especially Partnerships for the Goals (2,158) have a very low number of publications, indicating that these areas still receive less attention in multi-representational learning model research. This condition indicates a great opportunity for further research development that can integrate aspects of the SDGs that are less explored, in order to support the achievement of sustainable development goals in a more comprehensive and inclusive manner.

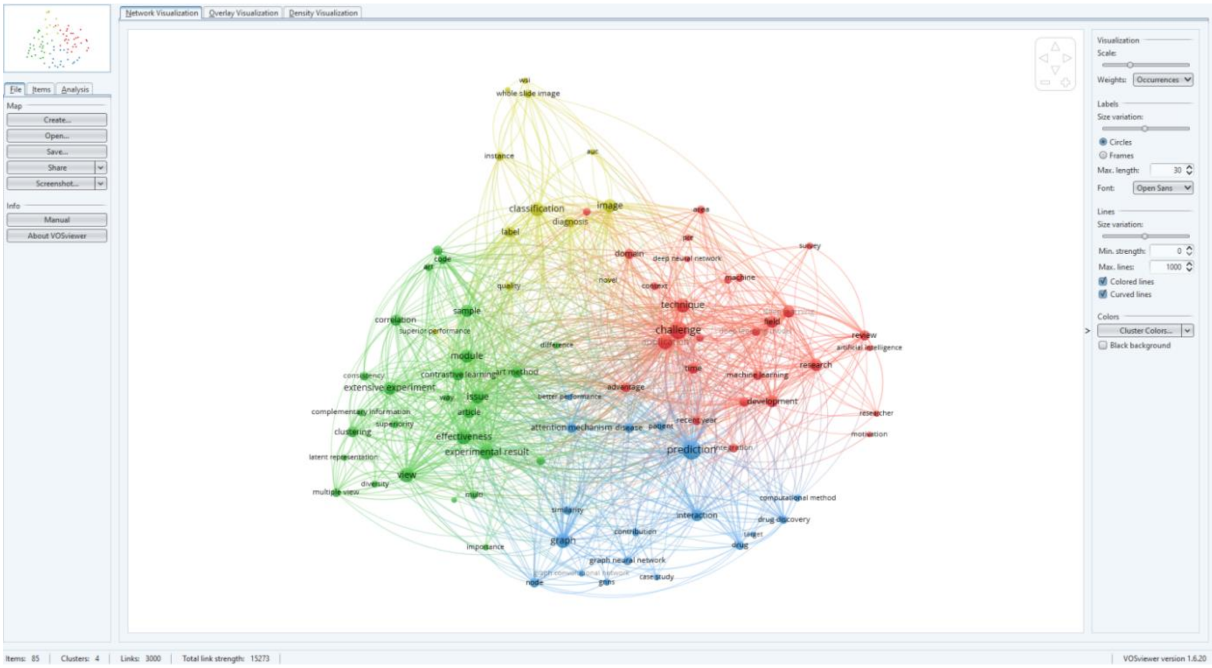

Figure 4. Network Visualization on Trend Multiple Representation Learning Model Research

Figure 4 shows a bibliometric visualization created using VOSviewer software, which represents the conceptual structure of a research field through the analysis of keyword co-occurrence. Each node on the map represents a keyword, while the connecting lines depict the co-occurrence relationships between keywords in the same document. The size of the node indicates the frequency of occurrence of the term, and the thickness of the line indicates the strength of the relationship between the terms. The visualization is divided into four colored clusters (red, green, blue, and yellow) that are automatically formed through a modularity-based clustering algorithm, allowing the grouping of keywords into interrelated conceptual themes (Van Eck & Waltman, 2010). The red cluster reflects issues related to challenges and methods in artificial intelligence and machine learning, as demonstrated by the keywords challenge, technique, and machine learning. The green cluster focuses on data experiments and validation, including the terms experimental result, clustering, and correlation, indicating a focus on evaluating model performance. The blue cluster relates to graph approaches in data processing and prediction, including applications in drug discovery, with the keywords graph, prediction, and network. Meanwhile, the yellow cluster focuses on image processing and classification, especially in the medical context, with terms such as whole slide image, classification, and diagnosis.

The analysis shows a total of 85 keywords, 3000 relationships between words, and a total strength of connection of 15,273, reflecting a dense concept network and close relationships between mapped concepts. This kind of visualization is very important in systematic literature reviews, because it can help researchers understand the scientific landscape of a field, identify dominant themes, and find potential new research gaps. By analyzing clusters and relationships between keywords, researchers can formulate further research directions that are more focused and scientifically meaningful. In this context, the research analyzed is in an interdisciplinary domain that combines artificial intelligence, deep learning, and image classification with real applications in the medical and pharmaceutical fields.

VOSviewer software is popularly used in bibliometric mapping due to its ability to present informative and structured visualizations based on large and complex scientific data (Van Eck & Waltman, 2010; Aria & Cuccurullo, 2017). The resulting visualizations not only show semantic relationships between concepts, but also serve as strategic tools in designing research directions for individual researchers as well as academic and research institutions.

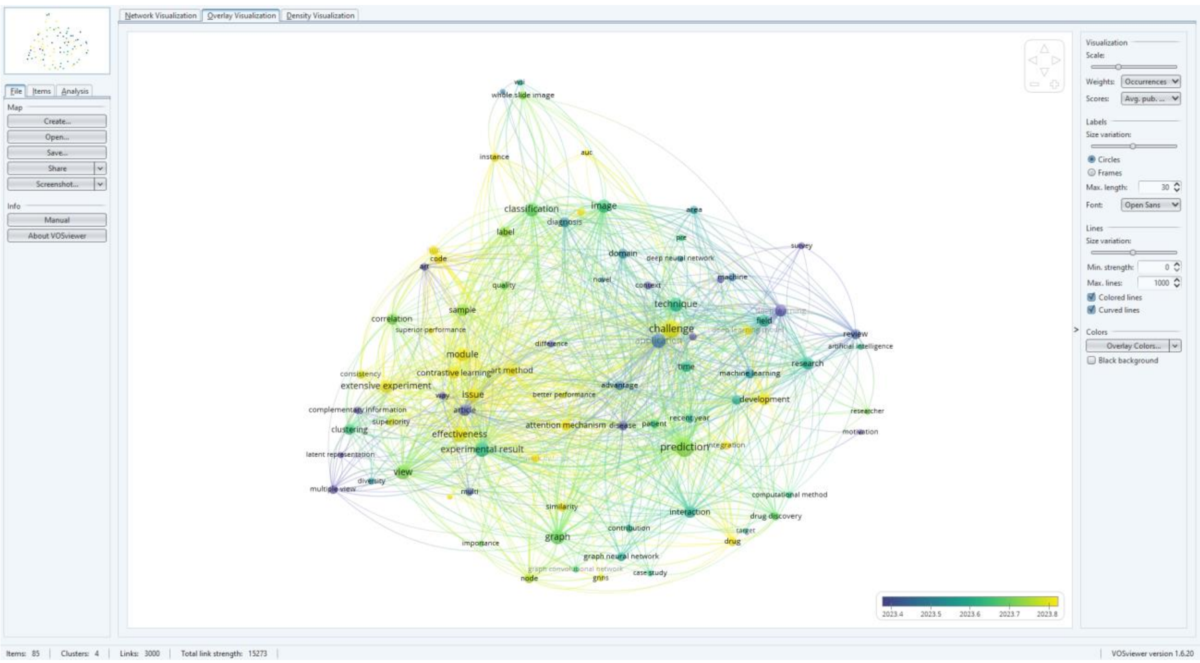

Figure 5. Overlay Visualization on Trend Multiple Representation Learning Model Research

Figure 5 presents a bibliometric visualization in the form of keyword mapping (keyword co-occurrence) using VOSviewer with the overlay visualization method, which shows the average publication time trend for each keyword. The color gradation on the map, from purple (keywords with older publication times) to yellow (keywords with newer publications), illustrates the dynamics of research development.

A total of 85 keywords are grouped into 4 clusters, forming a total of 3000 links with a total link strength of 15,273. The size of the node describes the frequency of keyword occurrence, with important terms such as challenge, technique, prediction, and experimental result dominating the center of the map, indicating a strong relationship and the prevalence of the concept in the literature. The color overlay shows the development of time, where yellow keywords such as module, attention mechanism, and drug discovery indicate topics that are relatively new or are receiving increasing attention in the current literature (around the second half of 2023). In contrast, terms such as classification or label appear earlier, which are represented by blue or light green.

This visualization is useful in identifying emerging research trends and conceptual relationships within a scientific domain, so that it can help researchers determine relevant and innovative research focuses (Van Eck & Waltman, 2010).

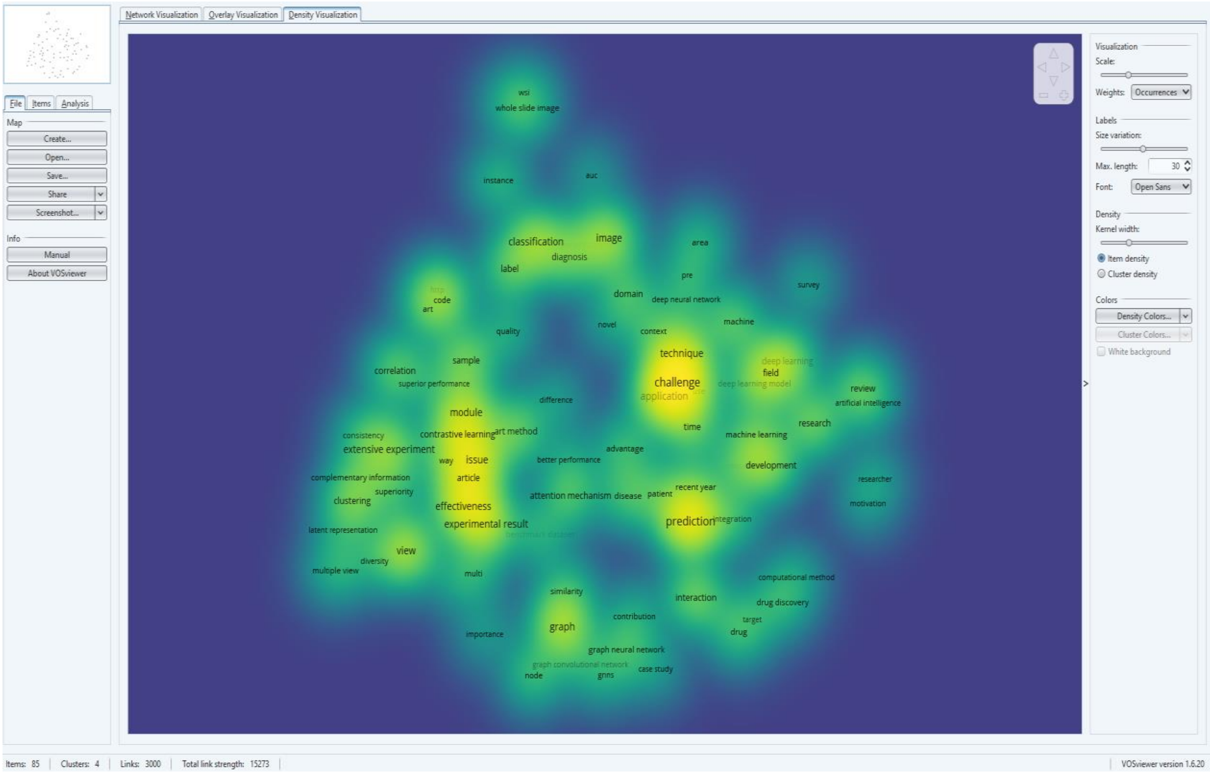

Figure 5. Density Visualization on Trend Multiple Representation Learning Model Research

Figure 6 shows the results of density visualization using VOSviewer, which illustrates the frequency and strength of relationships between important terms in a collection of scientific documents. Yellow indicates areas with the highest concentration, namely high term frequency, while green to blue colors depict areas with lower density.

This map serves as a tool to identify key terms, research trends, and relationships between topics in a particular field of study (Van Eck & Waltman, 2010). Terms with high density include challenge, technique, application, prediction, and effectiveness, indicating a research focus on technical challenges, engineering innovation, and evaluation of the effectiveness of model application in artificial intelligence. The emergence of terms such as deep learning, graph, interaction, classification, and image emphasizes the research focus on data-based approaches, especially in image and network analysis. There are a total of 85 terms, with 4 main clusters, 3000 links, and a total link strength of 15,273, indicating a high level of connectivity and concept integration.

This density visualization not only provides an overview of the main focus of research, but also helps researchers and stakeholders in identifying potential research gaps and collaboration opportunities in the same field (Perianes-Rodriguez et al., 2016).

Previous research, Justi and Gilbert (2002) emphasized that multiple representations not only function as learning aids, but also as effective pedagogical strategies in identifying and correcting students' misconceptions. When students are faced with multiple representations, they are encouraged to reflect and evaluate their understanding, resulting in a more accurate reconstruction of knowledge. Therefore, the multiple representation learning model is one of the important trends in science education that contributes to improving the quality of learning from elementary to college levels.

This study provides an important contribution to understanding the development and direction of research related to multi-representational learning models during the period 2016 to 2025. By identifying publication trends, primary sources, and collaboration patterns of researchers, this article not only enriches the academic treasury in the field of education but also provides practical insights for educators and curriculum developers. The findings produced can be the basis for the development of more effective and innovative learning strategies, especially in utilizing various forms of representation to improve students' conceptual understanding. In addition, the results of this study open up opportunities for further research that is more in-depth and focused on certain aspects of the multi-representational learning model, so that it can encourage the progress of education that is more adaptive and responsive to the needs of the times.

CONCLUSION AND SUGGESTION

This study successfully identified and described research trends related to multi-representational learning models during the period 2016 to 2025 using various data analysis methods from Dimensions.ai and Google Scholar processed through PoP and analyzed using VosViewer. The results of the analysis show a significant increase in the number of publications, variations in publication types, and increasingly intensive collaboration between researchers in this field. These findings provide a comprehensive picture of the focus and direction of research development, which emphasizes the importance of multi-representational learning models as an effective approach in improving students' conceptual understanding through various forms of representation. Thus, this article enriches the academic literature while providing a strong foundation for the development of more innovative and adaptive learning practices.

Based on the results of this study, it is recommended that further research can further explore specific aspects of the multi-representation learning model, such as the effectiveness of using certain combinations of representations in different learning contexts, as well as their impact on student learning outcomes quantitatively and qualitatively. In addition, educators and curriculum developers are expected to utilize these findings to design more varied and contextual learning strategies, so as to increase student engagement and understanding as a whole. Finally, education policymakers also need to consider supporting research and implementation of this learning model so that it can be widely and sustainably adopted in national and international education systems.

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AUTHOR CONTRIBUTIONS

Prelia Dwi Amanah (PA) is responsible for the article writing, data collection, analysis, and editing in this study. Nurhidayat Martin (NM) conducted a

literature review and development of the research methodology. Prof. Dr. Joni Rokhmat (JR) acted as a supervisor who provided academic guidance, strategic direction, and reviewed and revised the article manuscript. The three authors actively collaborated in the interpretation of the research results and the preparation of the final manuscript. All authors approved the final version of the article and take full responsibility for the accuracy of the content and integrity of this study.

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