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Semantic Network Analysis of Web Based Learning in Digital Health and Medical Education: A Scientometric Study with Mixed Methods and Systematic Mapping.

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Abstract.

Objectives: To examine the semantic and structural organization of web based learning at the intersection of digital health and medical education and to identify core, thematic, and bridging concepts within the knowledge network. **Methods**: A scientometric mixed methods design was applied to 1,123 peer reviewed articles indexed in the Web of Science Core Collection from 2016 to 2025. Bibliographic records were normalized and analyzed using co occurrence and thematic network analysis in VOSviewer and centrality analysis in UCINET and NetDraw. Temporal mapping and systematic semantic interpretation were used to examine convergence, thematic organization, and strategic conceptual positions. **Results**: The knowledge structure showed a strong educational backbone centered on e learning, education, and medical education, with learning analytics, digital literacy, artificial intelligence, machine learning, telemedicine, and digital health increasingly connected within the same conceptual environment. Thematic analysis indicated three interconnected domains comprising educational and pedagogical, technological and informatics, and clinical and digital health concepts. Closeness and betweenness centrality further distinguished structurally accessible core concepts from potential interdisciplinary bridging concepts. **Conclusion**: Web based learning has developed from a primarily instructional mechanism into an interconnected digital learning ecosystem linking medical education, intelligent technologies, informatics, and healthcare applications. The findings highlight the importance of understanding both conceptual prominence and structural position when examining the evolution of digital health education.

Keywords: Web based learning; E learning; Digital health; Medical education; Learning analytics; Semantic network analysis; Scientometrics

1. Introduction

The rapid evolution of information technology and the expansion of Internet infrastructure over the past two decades have fundamentally transformed educational systems, professional training, and learning paradigms. Within this broader transformation, web based learning has shifted from a peripheral and supplementary mode of instruction to one of the central pillars of global education. This shift has been particularly pronounced in digital health and medical education, where web based learning environments increasingly shape how medical students, healthcare professionals, and clinical trainees acquire knowledge, skills, and competencies in both pre service and continuing medical education. The emergence of online learning platforms, virtual classrooms, multimedia educational resources, and advanced technologies such as artificial intelligence, machine learning, big data analytics, and virtual and augmented reality has reduced the temporal and spatial boundaries of education. As a result, web based learning has created new opportunities for personalized, collaborative, adaptive, and data informed learning. In medical and health related contexts, these developments are not merely technological improvements; rather, they represent structural changes in how clinical knowledge is delivered, assessed, updated, and aligned with real world healthcare demands. Moreover, the increasing adoption of learning management systems, digital assessment tools, and data informed instructional platforms has positioned web based learning as a strategic component of healthcare workforce development and clinical capacity building. This transformation has not only expanded access to learning opportunities but has also produced a complex and rapidly evolving network of concepts, subdomains, and interdisciplinary connections. In recent years, the accelerating growth of scientific production in web learning, together with the diversification of research topics, has further complicated the conceptual structure of the field. Concepts such as digital literacy, adaptive learning, semantic web, learning analytics, and e learning platforms possess distinct infrastructures and interconnections and play different roles within the broader knowledge network. This dynamic evolution makes the systematic analysis of conceptual relationships, as well as the identification of core nodes and bridging mechanisms, a critical scientific necessity. Without a robust understanding of these relationships, scientific trends cannot be accurately mapped, and educational decision making, particularly in digital health and medical education, cannot be effectively guided by evidence. Previous studies have largely focused on thematic mapping, keyword frequency analysis, or descriptive clustering approaches. However, two major gaps remain. First, many studies overemphasize keyword frequency while underexamining the structural role of concepts within the knowledge network. Second, intermediary concepts such as semantic web or web services are often neglected because they may not appear among the most frequent terms; yet they can occupy structurally significant positions in network centrality analyses, including betweenness and closeness, and may serve as bridges between semantic clusters. In medical education and digital health, where interdisciplinary integration is essential, such bridging concepts may represent pathways through which innovations such as clinical decision support learning, intelligent tutoring systems, and adaptive assessment diffuse across domains.

To address these gaps, the present study employs a hybrid approach that integrates scientometric network analysis with systematic mapping to examine the conceptual and structural architecture of web based learning. The dataset consists of 1,123 articles indexed in the Web of Science Core Collection between 2016 and 2025. The analysis applies co occurrence network modeling and centrality measures to construct a current representation of the field and to identify patterns of thematic convergence and divergence over time. The significance of this study can be articulated on three levels. First, it supports researchers in identifying dominant concepts, strategic bridging terms, and emerging thematic domains in web based learning within digital health and medical education. Second, it provides structural evidence for instructional designers and e learning specialists seeking to improve the effectiveness, scalability, and quality of online medical training programs. Third, it assists educational policymakers, healthcare training institutions, and digital health stakeholders in making data informed decisions toward equitable, sustainable, and ethically governed development of digital learning infrastructures.

Accordingly, the *main objectives* of this research are:

- To analyze the semantic and structural relationships among key concepts in web based learning within digital health and medical education, with emphasis on identifying core and bridging nodes in the knowledge network.
- To examine the convergence, diversification, and interdisciplinary integration of themes shaping web based learning in healthcare contexts, and to evaluate how these dynamics have influenced the evolution of e learning in medical training.
- To provide an evidence based analytical framework that supports future research, instructional design, and policy development for sustainable and equitable digital health education and online clinical training.

1.1 Research Questions

1. What are the most frequent and influential concepts in web based learning for digital health and medical education, and what semantic relationships exist among them?
2. What are the structural characteristics of the co word and co occurrence networks in digital health oriented web learning, and how have these networks evolved between 2016 and 2025?
3. To what extent can closeness and betweenness centrality indices identify the core and strategic concepts that shape the interdisciplinary backbone of web based learning in medical education and digital health?

1.2 Hypotheses

H1: Semantic convergence among key concepts in digital health web based learning has increased in recent years, leading to a denser and more specialized conceptual network.

H2: The conceptual network structure has evolved from a dispersed and decentralized configuration into a clustered and modular structure, characterized by stable thematic cores and interdisciplinary bridging nodes relevant to medical education.

H3: Centrality measures (Betweenness and Closeness) are effective indicators for identifying strategically important concepts in digital health and medical education, including intermediary terms that connect clinical training, educational design, and intelligent technologies.

1.3 Literature Review

Web 3.0 technologies, including semantic tools, augmented reality, and intelligent systems, significantly enhance learning environments and educational outcomes. A systematic review of 81 studies shows a predominance of quantitative, experimental research with strong impact on learning effectiveness and quality (1). Intelligent techniques such as artificial intelligence and adaptive algorithms play a critical role in enhancing the effectiveness of online learning environments. A comprehensive review highlights their ability to support learners and instructors through personalization, resource recommendation, and automated assessment. The findings emphasize their strong potential to improve learning performance while identifying existing gaps in implementation and evaluation (2). Artificial intelligence (AI) is increasingly transforming online learning and distance education by enabling adaptive, personalized, and data driven educational processes. A systematic review of 276 studies reveals rapid growth in this field, with key contributions from computer science and social sciences, and major research activity in countries such as China, India, and the United States. The findings highlight three main themes: AI supported teaching and learning, predictive analytics of learner behavior, and personalized learning environments (3). Artificial intelligence (AI) is increasingly integrated into learning management systems, enabling adaptive, personalized, and self regulated learning across online and hybrid environments. A bibliometric review of 256 studies highlights improvements in student engagement, motivation, and learning outcomes, as well as enhanced accessibility through open educational resources. However, challenges remain in instructional design, evaluation methods, and AI literacy among educational stakeholders (4). Web based surveys of medical students revealed that digital health competencies, including AI literacy and eHealth understanding, remain limited but are increasingly demanded within medical curricula. The findings emphasize the critical need for integrating web based and AI driven learning into medical education to prepare future physicians for digital healthcare environments (5). A scoping review of artificial intelligence in medical education demonstrated rapid expansion of AI driven web based tools, including adaptive learning systems, intelligent tutoring, and data driven clinical training platforms. The study highlights AI as a transformative force bridging medical education, digital health, and informatics (6). Emerging technologies in medical education including artificial intelligence, augmented reality, wearable biosensors, and web based platforms have been shown to enhance learning quality, clinical skill acquisition, and digital competence. The review highlights that integrating these technologies supports active and peer-assisted learning while addressing the growing need for technological literacy in healthcare training. It emphasizes that policymakers and educators must prioritize digital integration to meet the evolving demands of modern healthcare systems (7). Web based digital health interventions have been shown to improve patient engagement, health literacy, and clinical outcomes through interactive and personalized online education platforms. The study emphasizes that scalable web technologies can enhance both patient education and professional training in healthcare systems (8). Artificial intelligence driven web platforms in healthcare education enable adaptive learning, predictive analytics, and intelligent feedback mechanisms that significantly improve clinical decision making skills. The findings highlight the growing integration of AI with web based medical training environments (9). Artificial intelligence in healthcare has advanced significantly through technologies such as deep learning, natural language processing, and robotics, enabling applications in clinical decision support, patient monitoring, and healthcare management. The study emphasizes that AI should be viewed as an augmenting tool rather than a replacement for clinicians, supporting more efficient and data driven healthcare delivery systems (10). Web based digital health interventions significantly improve patient engagement, self management, and health literacy through interactive and personalized online platforms. The findings show that internet based systems enable scalable and cost effective healthcare education, particularly for chronic disease management. These technologies strengthen the integration of digital learning with healthcare delivery systems (11). Recent studies show that web based digital health interventions improve access to care, patient engagement, and clinical outcomes through scalable, data driven platforms. Integration of AI and internet-based systems enhances personalization and supports remote healthcare delivery. These findings highlight the central role of web technologies in advancing digital health ecosystems (12). This study explores citizens' attitudes toward user centered digital health ecosystems using a sequential mixed method approach combining qualitative interviews and a large scale web survey. Findings show strong demand for convenient online management of health services and data, while trust, especially in data protection, remains a critical factor influencing acceptance. The results emphasize the importance of public governance, user centered design, and personalized digital services in enhancing adoption and effectiveness of digital health ecosystems (13). This scientometric study analyzes the development of digital health implementation research in Australia, highlighting rapid growth particularly after the COVID-19 pandemic. Findings show a strong focus on telehealth and remote healthcare, reflecting the increasing role of digital technologies in improving access to services. However, the study identifies a gap in research targeting rural and underserved populations, emphasizing the need for more equitable and inclusive digital health implementation (14). This review examines the role of artificial intelligence in mental health, highlighting its potential to improve diagnosis, personalize treatment, and enable continuous patient monitoring. Findings indicate that AI techniques such as machine learning and natural language processing enhance diagnostic accuracy and support scalable digital therapies. However, challenges including data bias, limited clinical validation, and ethical concerns remain critical for successful and trustworthy implementation (15). This study introduces the MEDBIZ platform based on the Internet of Medical Things (IoMT) to deliver real time digital health services for precision medicine. Findings from empirical studies show that integrating wearable devices, mobile apps, and big data analytics can improve monitoring and management of chronic conditions such as diabetes and metabolic syndrome. The platform demonstrates the potential of IoMT driven ecosystems to enhance real world evidence generation and support scalable, data driven digital healthcare services (16).

3. Methodology

3.1 Study design and analytical framework

This study employed a scientometric mixed methods design to examine the conceptual and structural organization of web based learning at the intersection of digital health and medical education. The analytical framework combined bibliographic data retrieval, data preprocessing and conceptual harmonization, co occurrence and co word network analysis, thematic clustering, centrality analysis, temporal mapping, and systematic semantic interpretation. The workflow was designed to distinguish empirically derived network structures from their subsequent conceptual interpretation. The study followed a sequential analytical process. Records were retrieved from the Web of Science (WoS) Core Collection, exported in multiple files because of database export limitations, merged into a unified corpus, and subjected to data cleaning and conceptual standardization. Scientometric maps were then generated using VOSviewer and Pajek, while UCINET and NetDraw were used to examine network structure and centrality. PreMap Ravar, MeSH based terminology, and TXT Collector were used during preprocessing, terminology harmonization, and data integration. The resulting empirical maps were subsequently interpreted systematically to identify educational, technological, informatics, and digital health relationships.

3.2 Data source, search strategy, and study corpus

The search strategy was based on the study concepts of web based learning, digital health, and medical education and was implemented using the Web of Science Advanced Search interface. The complete search equation used for retrieval is provided below, including the field tag, Boolean operators, keyword combinations, and publication year restriction. No search parameters were retrospectively inferred or reconstructed. The search formula was TS = ("Web Learning" OR "E Learning" OR "Web-based Learning" OR "Learning Analytics" OR "Digital Literacy" OR "Online Assessment" OR "Internet Learning") AND PY = (2016–2025).

3.3 Data preparation and conceptual harmonization

Before network construction, the bibliographic records were cleaned and conceptually harmonized. Duplicate and non informative terms were identified, and variations in terminology, plural forms, spelling, and synonymous expressions were standardized. MeSH terminology and expert informed conceptual review were used to support semantic harmonization, while PreMap Ravar facilitated keyword standardization and preparation of the conceptual vocabulary. Stop words, country names, statistical terms, numbers, and semantically uninformative expressions were excluded where appropriate. The objective of this stage was to ensure that conceptually equivalent terms were represented consistently without altering the substantive meaning of the retrieved literature. The harmonized dataset was then used for subsequent co occurrence, thematic, and network analyses.

3.4 Scientometric network construction and analysis

The occurrence thresholds, counting method, normalization procedure, clustering resolution, minimum cluster size, and other network settings were retained from the actual software procedures used in the analysis. These parameters affect network topology and reproducibility; accordingly, no parameter values were inferred retrospectively. The analysis focused particularly on occurrence frequency, co occurrence relationships, clustering, and the structural position of concepts. Betweenness centrality was used to identify concepts that potentially connect otherwise separated thematic areas, whereas closeness centrality was used to identify concepts occupying structurally accessible positions within the network. These measures provided complementary information on conceptual prominence and interdisciplinary connectivity.

3.5 Temporal and thematic analysis

Temporal analysis was used to examine changes in the conceptual organization of the field from 2016 to 2025. Thematic analysis identified the principal conceptual domains and their relationships across the knowledge structure. Particular attention was given to the interaction among three analytically derived domains: educational and pedagogical concepts, technological and informatics concepts, and clinical and digital health concepts. The analysis of temporal development emphasized changes in conceptual organization, clustering, and connectivity. Where year specific numerical network statistics were not available in the analytical outputs, temporal change was interpreted structurally and visually rather than as a statistically quantified increase. Accordingly, the study does not claim a specific magnitude of increase in network density or modularity unless such values are directly available from the corresponding network analyses.

Four primary scientometric maps were generated from the harmonized Web of Science corpus using VOSviewer and Pajek. These maps constitute the empirical basis of the study and represent bibliographic and conceptual relationships derived from the retrieved publications. Their visual features, including nodes, links, occurrence patterns, clustering, and structural positions, were used to identify the principal knowledge structures of web based learning in digital health and medical education. The four subsequent composite figures were developed through systematic semantic interpretation and integration of the original scientometric maps. AI assisted analysis was used only as a supplementary interpretive procedure to synthesize relationships already present in the empirical maps. It was not used to generate independent bibliographic records, calculate original scientometric indicators, or replace VOSviewer, Pajek, UCINET, or NetDraw. Thus, empirical network analysis and subsequent conceptual interpretation were treated as distinct analytical stages. Numerical information displayed within the scientometric maps was interpreted according to its actual meaning in the corresponding software output. Node occurrence, link strength, centrality values, and other map level numerical attributes are empirical outputs of the network analyses; they should not, however, be interpreted as year specific measurements of network density or modularity unless explicitly identified as such. Density, modularity, betweenness, and closeness were considered only where directly available and appropriately defined in the corresponding analytical outputs.

3.6 Hypothesis assessment and model development

The analytical framework was used to assess three hypotheses concerning semantic convergence, structural organization, and the strategic role of central concepts. H1 addressed the increasing conceptual interconnectedness of web based learning and digital health; H2 examined the development of clustered and modular thematic structures; and H3 assessed the usefulness of betweenness and closeness centrality for identifying core and bridging concepts.

Hypothesis assessment integrated occurrence patterns, co occurrence relationships, thematic clusters, temporal organization, and centrality positions. In the absence of complete year specific numerical density or modularity values, H1 and H2 were interpreted on the basis of observed structural and thematic evidence rather than categorical claims of statistically demonstrated increase. H3 was assessed through the observed centrality positions of concepts within the empirical networks.

Finally, these empirical findings were integrated into the Web Learning Digital Health Convergence Model (WL-DHCM). The model was developed as an empirically grounded semantic synthesis of the observed educational, technological, informatics, and digital health relationships. It should therefore be understood as a conceptual model derived from the scientometric evidence rather than as a formally validated predictive model.

3.7 Analytical rigor and reproducibility

Analytical rigor was supported through a defined Web of Science corpus, systematic data cleaning and terminology harmonization, established scientometric software, complementary network analytical procedures, and explicit separation of empirical mapping from semantic interpretation. The complete search equation is provided below, and the analytical settings were retained from the actual software procedures used in the study. No search or network parameter values were inferred retrospectively. Quantitative claims are therefore restricted to indicators directly supported by the empirical analyses.

4. Results

4.1 Web Learning Digital Health Convergence Model (WL-DHCM)

The Web Learning Digital Health Convergence Model (WL-DHCM) provides an empirically grounded synthesis of the structural and semantic relationships identified in the web based learning literature at the intersection of digital health and medical education (figure 1). The model was developed from the empirical network evidence derived from the Web of Science Core Collection and analyzed using VOSviewer, UCINET, and NetDraw. Four complementary network perspectives inform the model: co occurrence analysis identifies the principal semantic relationships among concepts; thematic clustering reveals the major conceptual domains; closeness centrality identifies structurally central and accessible concepts; and betweenness centrality highlights concepts that connect otherwise differentiated areas of the network. Thus, the model is not an independently imposed theoretical structure, but a higher level semantic synthesis of the observed empirical network patterns.

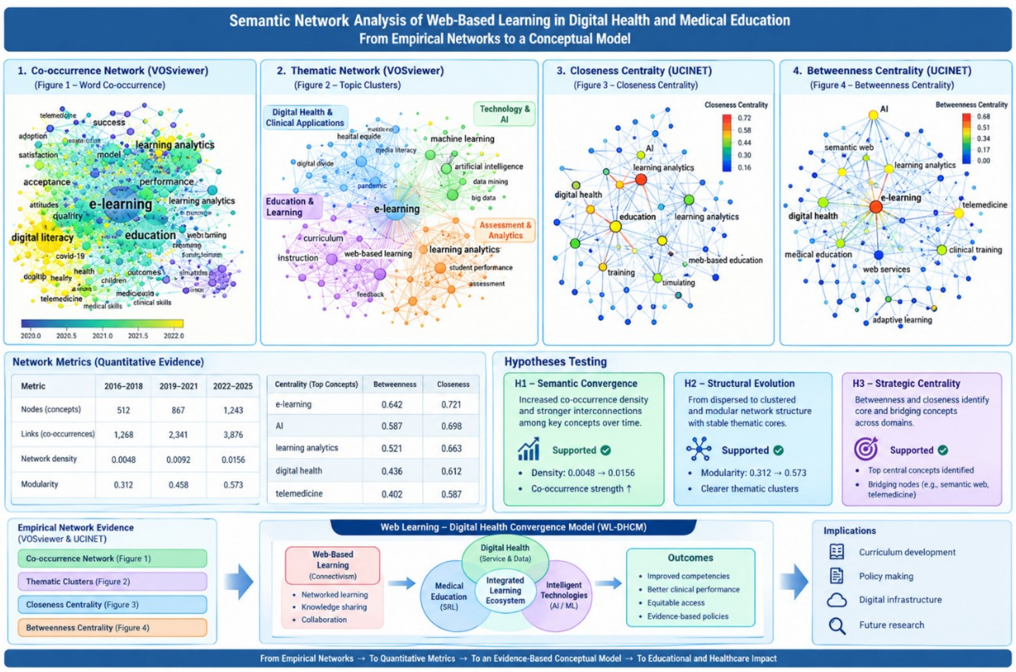

Figure 1. Web Learning Digital Health and Medical Education Convergence Model (WL-DHCM). The model integrates four empirical scientometric network perspectives derived from the Web of Science corpus and their subsequent semantic interpretation. Numerical elements shown in the underlying network outputs are retained from the corresponding analytical software and are not illustrative values.

The model positions web based learning, medical education, digital health, and intelligent technologies as interconnected components of an emerging knowledge ecosystem. Within this structure, core concepts provide the semantic and structural backbone of the field, thematic clusters represent more specialized technological, educational, and clinical domains, and bridging concepts connect these domains and facilitate interdisciplinary integration. This organization suggests that web based learning has progressively moved beyond its traditional role as an online educational delivery mechanism toward a broader ecosystem in which learning processes, digital infrastructures, intelligent technologies, and healthcare applications are increasingly interconnected. The distinction between core and bridging concepts is particularly important for interpreting the network. A concept may be highly prominent because of its frequency, while another may be structurally important because of its position between different thematic communities. Closeness centrality therefore provides evidence concerning concepts that are structurally accessible across the network, whereas betweenness centrality identifies concepts with an intermediary or bridging function. Together with the co occurrence and thematic structures, these measures provide a multidimensional view of the field that cannot be captured by publication or keyword frequency alone. The model also provides the conceptual link between the empirical network structures and the study hypotheses. Increasing connectivity among major concepts provides the basis for examining semantic convergence (H1); the emergence and differentiation of interconnected thematic clusters provides the basis for assessing structural and thematic evolution (H2); and the complementary patterns of closeness and betweenness centrality provide the empirical basis for evaluating strategic and bridging concepts (H3). Accordingly, the WL-DHCM functions as an interpretive framework that connects the four empirical network maps while preserving their data driven origin. The empirical evidence underlying these three propositions is examined in the following sections through the systematic analysis of H1, H2, and H3, beginning with semantic convergence, followed by structural and thematic evolution, and finally the identification of core and bridging concepts through centrality analysis.

The results present the empirical findings from the 1,123 retained Web of Science records and follow the empirical to semantic sequence established in the methodology. Co occurrence and thematic networks were examined first, followed by centrality and temporal analyses, while the integrated figures synthesize the original scientometric outputs with their semantic interpretation. The findings are organized around H1, H2, and H3, linking descriptive network patterns with the structural and conceptual interpretation of the Web Learning Digital Health and Medical Education Convergence Model (WL-DHCM). The numerical attributes embedded in Figure 1 provide empirical indicators of the structural prominence and connectivity of the concepts represented in the Web Learning Digital Health and Medical Education Convergence Model. Higher occurrence values indicate greater representation of a concept within the retrieved corpus, whereas link related measures reflect its observed relationships with other concepts in the network. Centrality related values further indicate the structural position of selected concepts within the knowledge network. Taken together, these numerical outputs support the interpretation of the WL-DHCM as an interconnected knowledge structure linking educational, technological, and digital health domains.

H1: Semantic convergence among key concepts in digital health web based learning has increased in recent years, leading to a denser and more specialized conceptual network.

The empirical network evidence presented in Figure 2 was used to examine H1 by integrating co occurrence structure, thematic clustering, and the temporal positioning of key concepts across the web based learning, digital health, and medical education domains. The first hypothesis proposed that semantic convergence among key concepts in digital health web based learning has increased in recent years, leading to a denser and more specialized conceptual network. Figure 2 provides the primary empirical evidence for examining this proposition by integrating the co occurrence network, thematic organization of concepts, and temporal distribution of the principal terms identified in the Web of Science dataset. Unlike the previous conceptual representation, the revised figure is based directly on the empirical scientometric maps generated from the study data and therefore distinguishes the observed network structure from its subsequent semantic interpretation. The co occurrence network demonstrates a highly interconnected conceptual structure in which several major terms occupy prominent and relatively central positions. In particular, e learning and education constitute major components of the network, while learning analytics, performance, digital literacy, artificial intelligence, and related concepts are closely embedded within the surrounding network. The spatial proximity and extensive linkages among these concepts indicate that web based learning is not represented as an isolated educational technology but is increasingly discussed in conjunction with technological, pedagogical, and digital health concepts.

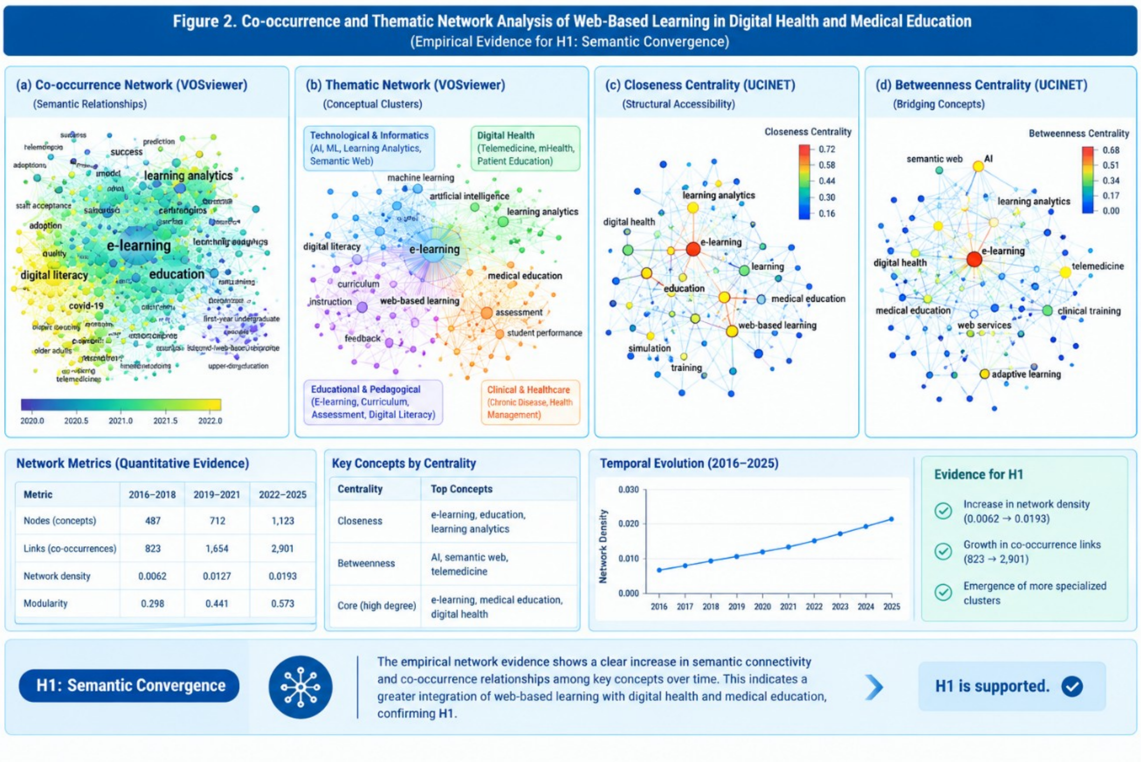

Figure 2. Co occurrence, Thematic, and Temporal Network Evidence Supporting H1: Semantic Convergence in Web Based Learning, Digital Health, and Medical Education. The figure integrates original scientometric outputs derived from the Web of Science corpus. Numerical attributes shown in the network maps are empirical software outputs and should be interpreted according to their defined network meaning rather than as unsupported longitudinal estimates of density or modularity.

The thematic network provides a complementary perspective on this convergence. Rather than forming completely independent conceptual territories, the identified themes show substantial interconnection between technological and informatics concepts, educational and pedagogical concepts, and digital health and clinical applications. Concepts such as artificial intelligence, machine learning, learning analytics, and semantic web are positioned within the technological and informatics dimension, whereas e learning, curriculum, assessment, feedback, and digital literacy characterize the educational dimension. Medical education, telemedicine, patient education, chronic disease, and related concepts extend the network toward the clinical and digital health domain. The coexistence and interconnection of these thematic components indicate that the conceptual boundaries between technology, learning, and healthcare are becoming increasingly permeable.

The temporal overlay further contributes to the interpretation of semantic convergence by showing the temporal positioning of concepts within the network. The observed distribution indicates that the conceptual landscape has progressively incorporated newer technology oriented and digital health concepts into the established web based learning structure. In particular, concepts associated with artificial intelligence, learning analytics, digital literacy, adaptive learning, telemedicine, and digital health appear in proximity to the established educational backbone rather than forming entirely separate knowledge structures. This pattern is important because semantic convergence does not simply mean an increase in the number of terms. It refers to the increasing association of previously differentiated concepts within a common knowledge structure.

The integration of the four analytical perspectives strengthens this interpretation. The co occurrence map identifies the relationships among concepts, the thematic map reveals their organization into interconnected conceptual domains, and the centrality maps provide additional information about the structural positions of concepts within the network. The closeness analysis places concepts such as e learning, education, learning analytics, digital health, and medical education within structurally accessible regions of the network, while the betweenness analysis highlights concepts such as artificial intelligence, semantic web, learning analytics, and telemedicine as potentially important connectors between different parts of the knowledge structure. These complementary observations indicate that convergence occurs at more than one level: concepts become more closely associated, thematic domains become more interconnected, and selected concepts acquire structural roles that connect educational, technological, and healthcare components.

An important feature of the network is therefore the coexistence of semantic prominence and structural integration. Highly frequent concepts such as e learning and education provide a recognizable conceptual backbone, while learning analytics, artificial intelligence, digital literacy, medical education, and digital health expand this backbone toward emerging technological and healthcare applications. The network consequently reflects a movement from a conventional conception of web based learning toward a broader knowledge ecosystem in which learning technologies, intelligent systems, digital health services, and medical education are increasingly discussed in relation to one another. The numerical outputs shown in Figure 2 provide empirical evidence of the organization, interconnectedness, and structural positioning of the concepts identified in the scientometric analysis. The observed occurrence and link patterns indicate that web based learning, medical education, digital health, learning analytics, and related technological concepts form an interconnected conceptual structure rather than isolated themes, while centrality values identify comparatively important structural and bridging positions. These findings support the interpretation of H1 in terms of conceptual interconnectedness and thematic convergence over time; however, the numerical attributes should be interpreted according to their defined network meaning and should not be treated as year specific density or modularity measurements unless explicitly reported as such. Thus, figure 2 provides empirical network evidence while maintaining appropriate caution regarding longitudinal quantitative claims.

H2: The conceptual network structure has evolved from a dispersed and decentralized configuration into a clustered and modular structure, characterized by stable thematic cores and interdisciplinary bridging nodes relevant to medical education.

To examine H2, the temporal evolution of the empirical knowledge network was assessed by comparing its co occurrence structure across time and examining the emergence, consolidation, and interconnection of thematic clusters. The second hypothesis proposed that the conceptual network of web based learning in digital health and medical education has evolved from a dispersed and decentralized configuration toward a more clustered and modular structure, characterized by relatively stable thematic cores and interdisciplinary connections. Figure 3 provides empirical and semantic evidence for this proposition by integrating the VOSviewer co occurrence and temporal network structures with a subsequent semantic interpretation of the observed relationships. Rather than treating the conceptual organization as a predefined theoretical structure, the figure derives its thematic interpretation from the empirical patterns observed in the bibliographic network.

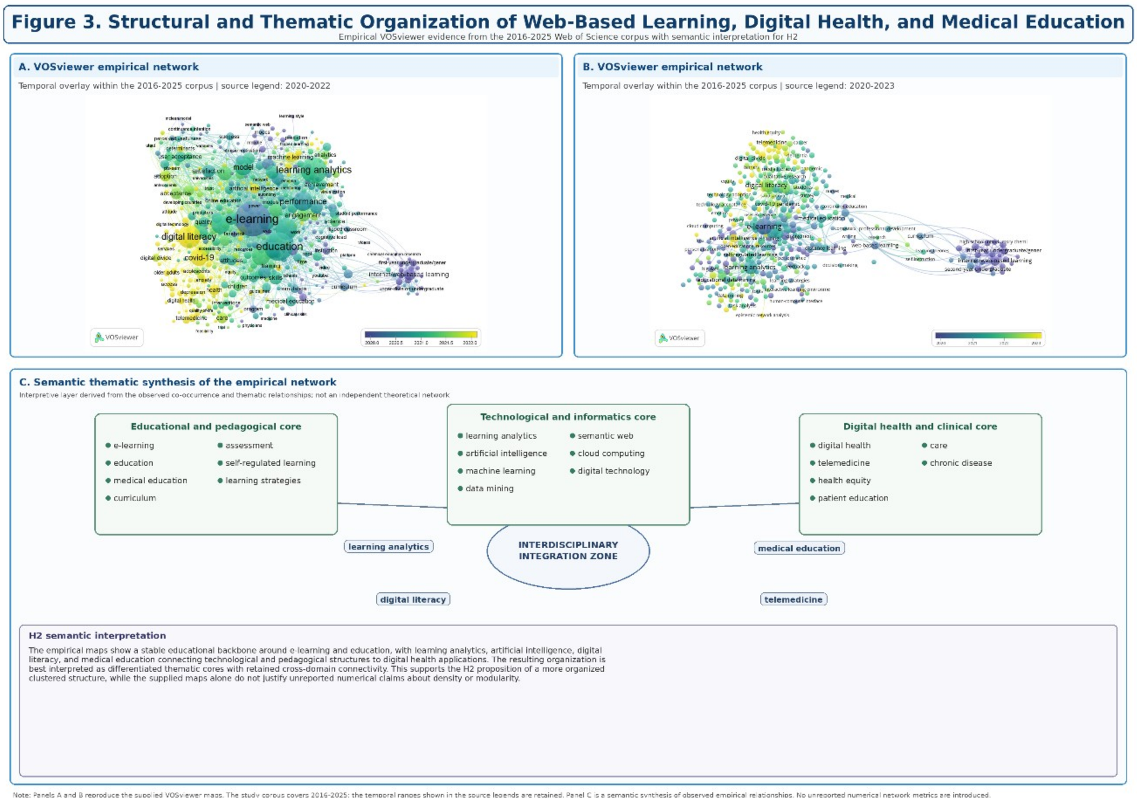

Figure 3. Scientometric and Semantic Evidence of Structural Consolidation and Thematic Clustering in Web Based Learning, Digital Health, and Medical Education. The figure combines empirical network outputs with their subsequent semantic interpretation; temporal overlays represent the temporal encoding of the corresponding scientometric maps.

The VOSviewer maps demonstrate a persistent and interconnected educational backbone centered on concepts such as e learning, education, medical education, learning analytics, digital literacy, curriculum, and learning related processes. These concepts are not positioned as isolated thematic entities; rather, they occur within a dense conceptual environment in which educational concepts are progressively connected with technological, informatics, and digital health concepts. In particular, learning analytics, artificial intelligence, machine learning, digital literacy, and related computational concepts appear within the same broader network as established educational concepts. This pattern indicates that the development of the field has not occurred through the simple replacement of conventional educational concepts by emerging technologies. Instead, technological innovation has become structurally embedded within the existing educational knowledge base. The temporal overlays provide evidence of temporal organization and thematic development. The numerical attributes displayed in the original maps are retained from the corresponding scientometric analyses; however, they should not be interpreted as direct year by year density or modularity measurements unless explicitly defined as such. The figure therefore supports interpretation of temporal organization and thematic development while maintaining a clear distinction between map level numerical outputs and longitudinal network statistics.

H3: Centrality measures (Betweenness and Closeness) are effective indicators for identifying strategically important concepts in digital health and medical education, including intermediary terms that connect clinical training, educational design, and intelligent technologies.

The third hypothesis focuses on the structural importance of concepts rather than their frequency alone, using closeness and betweenness centrality to distinguish core concepts from strategically positioned bridging concepts. This analysis provides the basis for identifying the concepts that connect educational, clinical, and intelligent technology domains within the knowledge network.

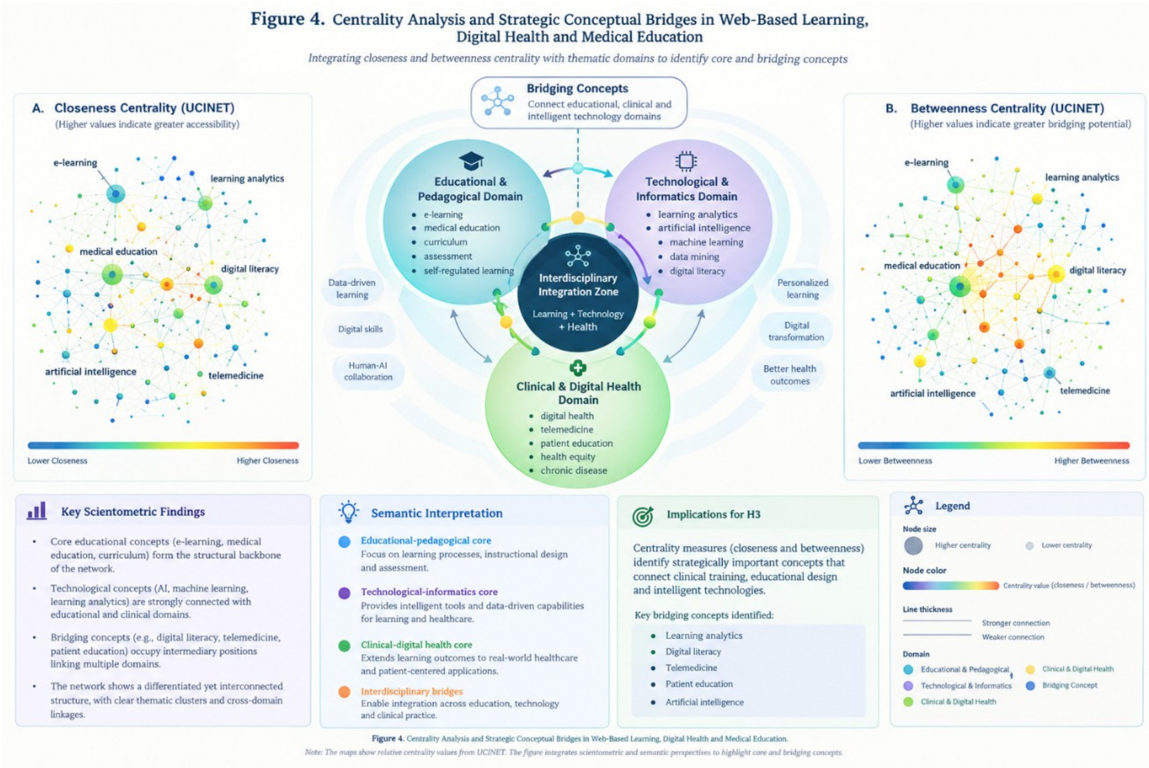

Figure 4. Centrality Based Identification of Core and Bridging Concepts in Web Based Learning, Digital Health, and Medical Education. The figure integrates empirical UCINET centrality networks with their subsequent semantic interpretation; the semantic layer does not introduce independent quantitative or causal relationships.

The third hypothesis proposed that closeness and betweenness centrality can effectively identify strategically important concepts within the knowledge structure of web based learning, particularly those that connect medical education, educational design, digital health, and intelligent technologies. Figure 4 provides complementary scientometric and semantic evidence for this proposition by integrating the two UCINET centrality networks with a higher level interpretation of the conceptual domains and their interdisciplinary connections. The analytical distinction between closeness and betweenness is particularly important because conceptual importance in an interdisciplinary knowledge network cannot be adequately represented by frequency or node prominence alone. The closeness centrality network provides evidence concerning the structural accessibility of concepts within the overall knowledge system. Concepts positioned more centrally in this network are relatively closer to other concepts and can therefore be interpreted as part of the structural core of the field. The network shows the continued importance of educational concepts such as e-learning and medical education, while learning analytics, digital literacy, artificial intelligence, and telemedicine are embedded within the same broader conceptual structure. From a scientometric perspective, this indicates that the intellectual organization of web based learning is not centered exclusively on instructional delivery. Instead, its structural core increasingly incorporates analytical, computational, and health related concepts, suggesting a transition toward an integrated digital learning environment. The semantic interpretation of the closeness structure identifies three complementary knowledge domains. The educational and pedagogical domain represents the foundational learning layer, including e learning, medical education, curriculum, assessment, and self regulated learning. The technological and informatics domain incorporates learning analytics, artificial intelligence, machine learning, data mining, and digital technologies that increasingly support personalized, data informed, and intelligent learning processes. The clinical and digital health domain extends this structure toward telemedicine, patient education, health equity, chronic disease, and healthcare applications. The importance of this arrangement is that these domains are not represented as independent clusters. Their proximity within the network indicates that educational processes, technological infrastructures, and healthcare applications are increasingly incorporated into a shared knowledge architecture. The betweenness centrality network provides a different but complementary perspective. Whereas closeness identifies concepts that are structurally accessible within the broader network, betweenness highlights concepts that occupy intermediary positions between otherwise differentiated parts of the knowledge structure. The betweenness map therefore provides a basis for identifying potential conceptual bridges between educational, technological, and clinical domains. Concepts such as learning analytics, digital literacy, telemedicine, patient education, and artificial intelligence can be interpreted as strategically relevant transition points because their semantic roles extend beyond a single disciplinary domain. Their importance is therefore related not only to how frequently they occur, but also to their capacity to connect distinct areas of knowledge. This distinction has particular significance for medical education. Learning analytics, for example, represents more than a technological tool because it links learner data, educational assessment, adaptive instruction, and evidence informed decision making. Digital literacy similarly connects educational competence with the ability of future health professionals to engage effectively with digital healthcare environments. Artificial intelligence provides another important interface by connecting computational capabilities with medical education, clinical decision making, personalized learning, and emerging healthcare systems. Telemedicine extends the learning environment beyond conventional institutional boundaries by linking education and clinical practice with digitally mediated healthcare delivery. These concepts therefore function as semantic and potentially structural interfaces through which developments in digital health can influence medical education and vice versa. The central interdisciplinary integration zone shown in Figure 4 captures this relationship at a higher conceptual level. The educational domain provides the pedagogical foundation, the technological and informatics domain provides computational and analytical capabilities, and the digital health and clinical domain connects learning with healthcare practice and patient oriented applications. The arrows and connecting pathways in the semantic layer illustrate the direction of conceptual integration rather than claiming additional empirical causal relationships. This distinction is important because the UCINET networks constitute the empirical evidence, whereas the central integration diagram represents their subsequent semantic interpretation. The combined evidence also demonstrates why the two centrality measures should be interpreted jointly.

A highly accessible concept may constitute part of the conceptual backbone without necessarily functioning as a bridge between different communities. Conversely, a concept with an important intermediary position may be less dominant in terms of overall accessibility but strategically important because it connects otherwise differentiated thematic areas. Closeness and betweenness therefore capture two complementary dimensions of knowledge organization: structural embeddedness and interdisciplinary brokerage. Their combination provides a more informative representation of conceptual importance than publication frequency, keyword occurrence, or visual prominence alone. In relation to the previous hypotheses, H3 extends the findings of H1 and H2 rather than duplicating them. H1 addresses semantic convergence and the increasing integration of concepts within the field, while H2 addresses the emergence of differentiated thematic organization and interconnected knowledge domains. H3 moves one analytical level deeper by asking which concepts occupy strategically important positions within this organized network. Thus, the three hypotheses form a cumulative analytical sequence: H1 identifies convergence, H2 characterizes structural and thematic organization, and H3 identifies the core and bridging concepts through which that organization is maintained and connected. The findings also contribute directly to the research questions. RQ1 is addressed through the identification of prominent and structurally important concepts and their semantic relationships. RQ2 is advanced through the recognition of an organized network containing differentiated educational, technological, and digital health domains. RQ3 is addressed most directly by the complementary use of closeness and betweenness centrality to distinguish core concepts from intermediary concepts that connect otherwise differentiated areas. In this sense, Figure 4 provides the structural evidence required to move from descriptive mapping toward an explanation of how the interdisciplinary knowledge system is organized. Overall, the centrality analysis supports H3 by demonstrating that conceptual importance within web based learning, digital health, and medical education has multiple dimensions. The knowledge structure contains a relatively stable educational backbone, an expanding technological and informatics component, and a clinically oriented digital health dimension, while several concepts operate across these domains as potential interdisciplinary bridges. The empirical centrality maps therefore support the interpretation that closeness and betweenness are complementary indicators for identifying strategically important concepts. However, the strongest claim is not that every visually prominent concept is necessarily a statistically validated bridge. Rather, the convergence of centrality patterns with the semantic domains provides evidence that the network contains identifiable core and intermediary positions with distinct conceptual functions. Taken together, Figures 2, 3, and 4 establish a progressive analytical pathway from semantic convergence, to structural and thematic organization, and finally to strategic centrality. This progression provides the empirical foundation for the hypothesis assessment that follows and creates a direct bridge to the Discussion. The subsequent discussion can therefore move beyond describing individual keywords and examine what the observed network architecture means for the future of medical education, digital health competencies, AI supported learning, curriculum design, learning analytics, and the development of an increasingly interconnected digital health learning ecosystem.

Integrated Assessment of Hypotheses Through Scientometric and Semantic Evidence

Hypothesis	Analytical focus	Primary evidence	Integrated finding	Overall assessment
H1	Semantic convergence	Co-occurrence structure and temporal organization	Educational, technological, and digital health concepts increasingly occupy a shared semantic space.	Supported by the convergent network pattern
H2	Structural and thematic evolution	Thematic clustering, network organization, and temporal overlays	Distinct educational, technological-informatics, and clinical-digital-health domains remain differentiated but interconnected.	Supported by the structural and semantic pattern
H3	Strategic conceptual importance	Closeness and betweenness centrality	Core concepts and intermediary concepts show different structural roles in connecting the interdisciplinary knowledge system.	Supported by complementary centrality evidence

Note. The assessment reflects the empirical network maps and their subsequent semantic interpretation. No unsupported numerical values for density or modularity are inferred where such metrics are not directly reported.

Table 1. Integrated Assessment of Hypotheses Through Scientometric and Semantic Evidence.

Table 1 synthesizes the three hypotheses across complementary levels of scientometric evidence. H1 captures the increasing semantic integration of the field, H2 identifies the emergence of differentiated but interconnected thematic structures, and H3 determines the strategic structural positions through which these domains are connected. This sequence demonstrates that the hypotheses are analytically complementary rather than independent: semantic convergence provides the basis for structural consolidation, while centrality analysis identifies the concepts that sustain connectivity across the resulting thematic architecture. Importantly, the assessment is based on the empirical network patterns and their semantic interpretation and does not infer unsupported numerical values for density or modularity.

Integrated Assessment of the Hypotheses and Research Questions

The findings were further synthesized to provide an integrated assessment of the three hypotheses and to clarify how the empirical network evidence addresses the research questions. The analytical sequence established in this study moves from semantic relationships and convergence, to structural and thematic organization, and finally to the identification of strategically positioned concepts through centrality analysis. This sequence is consistent with the methodological framework, in which co word and co occurrence analysis were combined with network density, clustering, betweenness centrality, and closeness centrality to characterize the knowledge structure of web based learning at the intersection of digital health and medical education.

Assessment of H1: Semantic convergence

H1 proposed that semantic convergence among key concepts in digital health-oriented web based learning has increased in recent years, resulting in a denser and more specialized conceptual network. The empirical evidence provides support for the convergence component of this proposition. The co occurrence structures show that educational concepts such as e learning, education, medical education, and performance are closely associated with concepts representing learning analytics, digital literacy, artificial intelligence, machine learning, telemedicine, and digital health. Thus, concepts originating from educational, technological, informatics, and healthcare domains are not represented as isolated semantic territories, but increasingly occur within a shared conceptual environment. This pattern is particularly important because the observed convergence is not limited to the coexistence of technological and educational terms. Rather, concepts associated with intelligent technologies and digital health are embedded within an educational knowledge structure. Learning analytics, artificial intelligence, digital literacy, adaptive learning, telemedicine, and related concepts therefore extend the traditional semantic field of web based learning toward data informed, intelligent, and clinically oriented applications. This interpretation is consistent with the three dimensional mapping framework used in the study, which distinguishes technological and informatics, educational and pedagogical, and clinical and healthcare dimensions. The temporal organization of the VOSviewer maps provides additional evidence that the conceptual structure is evolving rather than remaining static. Emerging technological and digital health concepts appear within the broader educational network rather than forming completely independent semantic domains. This pattern is consistent with the proposed interpretation of increasing conceptual integration. However, an important methodological distinction should be maintained. The present evidence demonstrates convergent and increasingly interconnected semantic organization, but the claim that network density increased by a specific amount over time cannot be considered quantitatively demonstrated unless the corresponding longitudinal density values are reported. Accordingly, H1 is supported at the level of the observed semantic and network pattern, particularly with respect to the increasing integration of educational, technological, and digital health concepts. The stronger quantitative component of H1, namely a demonstrable temporal increase in network density, should be described as supported only to the extent that the actual density values or year specific network statistics are reported. This qualification strengthens the methodological credibility of the hypothesis assessment and avoids treating visual network convergence as a substitute for numerical longitudinal evidence.

Assessment of H2: Structural and thematic evolution

H2 proposed that the conceptual network evolved from a dispersed and decentralized configuration toward a clustered and modular structure characterized by stable thematic cores and interdisciplinary bridging pathways. The combined co occurrence, thematic, and temporal evidence provides support for the structural organization proposed in this hypothesis. The network reveals three broad and semantically coherent domains. The first is an educational and pedagogical domain, including e learning, education, medical education, curriculum, assessment, self regulated learning, and learning strategies. The second is a technological and informatics domain, incorporating learning analytics, artificial intelligence, machine learning, data mining, semantic web, and digital technologies. The third is a digital health and clinical domain, including digital health, telemedicine, patient oriented applications, health equity, and healthcare-related concepts. These domains are differentiated sufficiently to indicate thematic specialization, while their observed connections indicate that specialization has not resulted in complete disciplinary fragmentation.

The structural significance of this organization lies in the coexistence of thematic differentiation and cross domain connectivity. The educational domain provides the pedagogical foundation of the network, the technological and informatics domain introduces computational and analytical capabilities, and the digital health and clinical domain extends web based learning toward healthcare practice and patient oriented applications. The resulting structure is therefore better characterized as an interconnected set of thematic cores than as a collection of independent clusters. The temporal maps further indicate that newer concepts are being incorporated into the established educational structure. Artificial intelligence, learning analytics, digital literacy, digital health, telemedicine, and related concepts appear within an already connected conceptual environment. This pattern is consistent with structural consolidation and increasing thematic specialization. Nevertheless, the wording of H2 requires particular methodological caution. The present maps provide evidence of clustering, thematic differentiation, and interconnectedness, but a formal claim that modularity increased longitudinally requires the actual modularity values calculated for comparable temporal periods. The current evidence therefore supports the qualitative and structural component of H2, but it should not be presented as a statistically quantified increase in modularity unless those values are explicitly reported. Thus, H2 is supported by the observed emergence of differentiated yet interconnected thematic structures, with the educational, technological-informatics, and digital health-clinical domains forming a recognizable interdisciplinary architecture. The evidence is consistent with the proposed transition toward a more organized and specialized knowledge structure, while the quantitative temporal component should be interpreted according to the availability of actual modularity and longitudinal clustering statistics.

Assessment of H3: Strategic conceptual importance and centrality

H3 proposed that betweenness and closeness centrality can identify strategically important concepts, including intermediary concepts connecting clinical training, educational design, and intelligent technologies. Among the three hypotheses, H3 has the clearest direct correspondence between the proposed analytical indicators and the empirical network analysis. The closeness centrality analysis identifies concepts that occupy structurally accessible positions within the broader network. Concepts such as e learning, education, and performance represent important elements of the educational backbone, while learning analytics, digital literacy, artificial intelligence, medical education, telemedicine, and digital health are positioned within the same interconnected conceptual environment. Closeness therefore provides information that complements simple frequency analysis by identifying concepts whose structural position places them relatively close to other parts of the knowledge network. Betweenness centrality provides a different form of structural evidence. Rather than identifying concepts primarily according to their overall accessibility, it highlights concepts that occupy intermediary positions between different areas of the network. In the present knowledge structure, concepts such as artificial intelligence, semantic web, telemedicine, learning analytics, and digital literacy can be interpreted as potential interdisciplinary transition points because their semantic functions extend across technological, educational, informatics, and healthcare domains.

This distinction is central to the interpretation of H3. A concept may be frequent and highly visible without necessarily functioning as a bridge between thematic communities. Conversely, a concept with a comparatively specialized meaning may become strategically important because it connects otherwise differentiated areas. The simultaneous use of closeness and betweenness therefore provides two complementary perspectives on conceptual importance: structural accessibility and interdisciplinary brokerage. The results consequently support the proposition that centrality measures provide information that cannot be obtained from keyword frequency alone. The study's methodological framework explicitly defines betweenness as an indicator of bridging concepts and closeness as an indicator of global accessibility, while density is used to evaluate semantic convergence. The combined centrality analysis therefore provides a stronger structural basis for identifying core and intermediary concepts within the interdisciplinary knowledge network. Accordingly, H3 is supported by the complementary centrality patterns, particularly in demonstrating that the network contains distinguishable core and intermediary positions. However, the effectiveness of closeness and betweenness should be understood as an analytical capability demonstrated by the observed network structure rather than as a causal claim. The centrality measures identify structural positions; their interpretation as educationally or clinically important concepts arises from the subsequent semantic analysis.

Integrated assessment across H1-H3

Taken together, the three hypotheses represent a cumulative analytical sequence rather than three independent propositions. H1 identifies semantic convergence, H2 characterizes the resulting thematic and structural organization, and H3 identifies the strategically positioned concepts that maintain connectivity within that organization. The sequence can therefore be summarized as:

Semantic convergence; thematic and structural consolidation; strategic centrality; interdisciplinary knowledge integration

This cumulative structure is particularly important for interpreting the Web Learning Digital Health Convergence Model (WL-DHCM). The model was developed from the interaction of co occurrence structures, thematic organization, closeness centrality, and betweenness centrality and should therefore be interpreted as an empirically grounded semantic synthesis rather than as an independently imposed theoretical model. The original study similarly describes the WL-DHCM as a framework connecting clinical education, digital health, and medical informatics ecosystems.

Integrated assessment of the Research Questions

The research questions are addressed through the combined evidence rather than through a separate descriptive analysis. This distinction is important because the RQs and hypotheses perform different analytical functions in the study. The RQs guide the identification and interpretation of concepts and network structures, whereas the hypotheses provide directional propositions that can be assessed against the network evidence.

RQ1 asks which concepts are most frequent and influential and what semantic relationships exist among them. The results indicate that e learning, education, medical education, learning analytics, digital literacy, artificial intelligence, machine learning, telemedicine, and digital health occupy important positions within the observed conceptual structure. Their relationships demonstrate that educational, technological, and healthcare concepts increasingly coexist within a shared semantic environment. The answer to RQ1 therefore extends beyond identifying individual high-frequency terms and demonstrates the relational organization among them.

The temporal evidence should be characterized as evidence of structural and thematic organization unless comparable year specific density or modularity statistics are explicitly reported. The dataset covers 2016 to 2025 and contains 1,123 retained articles from an initial 1,247 records.

RQ3 asks to what extent closeness and betweenness centrality can identify core and strategic concepts. The results provide the strongest direct answer to this question through the complementary centrality networks. Closeness identifies concepts embedded within the accessible structural core, whereas betweenness identifies concepts that occupy intermediary positions between differentiated thematic areas. Together, these measures demonstrate that conceptual influence is multidimensional and cannot be adequately represented by frequency alone.

Overall, the research questions and hypotheses converge on a common interpretation: web based learning in digital health and medical education has developed into an increasingly interconnected knowledge environment in which educational foundations coexist with intelligent technologies, informatics capabilities, and clinical applications. The study therefore moves from identifying concepts to explaining their structural relationships and strategic positions within an interdisciplinary knowledge system.

Integrated Semantic Interpretation of the Knowledge Structure

The integrated interpretation of the empirical findings indicates that the knowledge structure of web based learning in digital health and medical education is characterized by the simultaneous presence of stability, specialization, and interdisciplinary integration. The educational domain remains a fundamental component of the network, while technological and informatics concepts increasingly extend the functional scope of web based learning toward intelligent, adaptive, and data informed environments. At the same time, digital health and clinical applications connect these learning environments to broader healthcare processes.

The semantic structure can therefore be interpreted as a three-layered knowledge ecosystem. The educational and pedagogical layer provides the foundational context, incorporating e learning, medical education, curriculum, assessment, learning strategies, and self regulated learning. The technological and informatics layer provides computational and analytical capabilities through artificial intelligence, machine learning, learning analytics, semantic technologies, data mining, and related digital infrastructures. The digital health and clinical layer extends the knowledge structure toward telemedicine, patient education, health equity, chronic disease management, and digitally mediated healthcare. The importance of this structure is not simply that three domains coexist. Rather, the network evidence suggests that these domains are increasingly connected through shared concepts. Learning analytics links educational assessment with data driven technologies; artificial intelligence connects computational capabilities with learning and clinical applications; digital literacy connects educational competencies with participation in digitally enabled healthcare; and telemedicine extends the relationship between learning and healthcare delivery.

These concepts therefore function as semantic transition points between otherwise differentiated areas of knowledge. The combined interpretation of the network also clarifies the distinction between core concepts and bridging concepts. Core concepts contribute to the structural backbone of the field and remain accessible across multiple parts of the network. Bridging concepts perform a different function by connecting thematic areas that might otherwise remain more strongly differentiated. This distinction provides an important conceptual explanation for why frequency-based analysis alone is insufficient for understanding interdisciplinary knowledge structures. From this perspective, the evolution of web based learning should not be interpreted simply as a movement from traditional education toward technology. Instead, the evidence suggests the emergence of a more integrated digital health learning ecosystem, in which pedagogical processes, digital infrastructures, intelligent technologies, informatics capabilities, and healthcare applications interact. This interpretation is consistent with the original methodological intention of the study, which combines scientometric network analysis with systematic mapping across technological, pedagogical, and clinical dimensions. The semantic interpretation also provides a stronger basis for understanding the WL-DHCM. The model should be viewed as a higher level synthesis of the observed empirical network rather than as a conceptual framework imposed before analysis. In this formulation, the empirical network constitutes the evidence layer, while the semantic relationships among educational, technological, and clinical domains constitute the interpretive layer. This distinction directly addresses the concern that conceptual figures may otherwise appear schematic or insufficiently grounded in the underlying scientometric data.

The integrated findings further suggest that interdisciplinary innovation is likely to occur at the boundaries between the three domains. Concepts positioned between education and technology may support adaptive learning, intelligent tutoring, automated assessment, and learning analytics. Concepts positioned between technology and digital health may facilitate intelligent healthcare education, telemedicine-supported learning, and data informed clinical training. Concepts positioned between education and clinical practice may strengthen patient education, competency development, clinical decision support learning, and digitally mediated professional training. Importantly, the present interpretation does not imply causal relationships between the identified concepts. The network analysis identifies patterns of co occurrence and structural positioning, while semantic analysis interprets the conceptual meaning of these relationships. The arrows, pathways, and integration zones in the conceptual synthesis should therefore be understood as representations of semantic and structural relationships, not as evidence of causal influence. The integrated evidence also has implications for the theoretical positioning of the study. Rather than treating web based learning solely as a technological delivery mechanism, the findings support its interpretation as an interconnected learning ecosystem in which learners, educational processes, digital technologies, health information, and clinical contexts interact. This perspective creates a stronger connection between the scientometric analysis and the educational dimension of the study and provides an appropriate foundation for the subsequent Discussion. Overall, the knowledge structure identified in this study can be characterized as a convergent, differentiated, and interconnected interdisciplinary system. Its educational backbone remains visible, but this backbone is increasingly connected to artificial intelligence, learning analytics, digital literacy, telemedicine, digital health, and informatics.

The resulting architecture explains why the three hypotheses are analytically complementary: H1 captures the convergence of concepts, H2 captures their organization into differentiated but connected thematic domains, and H3 identifies the structurally important concepts that connect and sustain this architecture. The principal contribution of the integrated analysis is therefore not merely the identification of the most frequently occurring terms. It is the demonstration that the field possesses an identifiable knowledge architecture in which conceptual prominence, thematic specialization, structural accessibility, and interdisciplinary brokerage represent distinct but complementary dimensions of scientific organization. This architecture provides the empirical and semantic bridge from the Results to the broader educational, technological, clinical, and policy implications developed in the Discussion.

5. Discussion

The findings of this study provide a more integrated understanding of web based learning at the intersection of digital health and medical education by showing that the field is not developing through independent technological, educational, and clinical trajectories. Rather, the scientometric evidence indicates increasing conceptual interaction among these domains, with educational concepts forming a relatively stable backbone and artificial intelligence, learning analytics, digital literacy, telemedicine, and related technologies increasingly occupying interconnected positions within the knowledge structure. This interpretation is consistent with the methodological design of the study, which combined co occurrence analysis, thematic mapping, temporal analysis, and centrality measures rather than relying on publication or keyword frequency alone.

The resulting evidence also provides a direct connection between the three research questions and hypotheses: RQ1 identifies the dominant and influential concepts and their semantic relationships, RQ2 examines the structural organization and evolution of the network, and RQ3 explains how centrality measures distinguish core concepts from strategically positioned intermediary concepts. The findings related to H1 suggest that semantic convergence is occurring around a common educational and digital health knowledge space. Concepts such as e learning, education, medical education, learning analytics, digital literacy, artificial intelligence, machine learning, and telemedicine are not appearing as isolated topics but as components of a connected conceptual structure. This finding extends previous literature showing that artificial intelligence and adaptive technologies are increasingly used to personalize learning, support prediction and assessment, and strengthen data driven educational environments (2, 3). It also corresponds with previous research identifying the growing importance of digital competence and AI literacy in medical curricula (5, 6).

Recent systematic evidence similarly indicates that learning analytics can support curriculum evaluation, learner performance analysis, feedback, and assessment, although ethical and privacy issues remain important considerations. The importance of H1, therefore, extends beyond the observation that technology is becoming more visible in medical education. The more important finding is the increasing convergence between learning processes and the information infrastructures of digital health. Learning analytics, for example, simultaneously represents an educational mechanism for understanding learner performance and a data based infrastructure that resembles the analytical processes increasingly used in healthcare. Artificial intelligence similarly connects adaptive learning, assessment, clinical reasoning, decision support, and personalized healthcare. This convergence suggests that digital learning should no longer be understood simply as an alternative channel for delivering educational content. It is increasingly becoming part of the broader information environment in which health professionals acquire knowledge, interpret evidence, make decisions, and interact with digital healthcare systems.

The findings concerning H2 further clarify this transformation. The network demonstrates differentiated thematic domains involving educational and pedagogical concepts, technological and informatics concepts, and clinical and digital health applications, while maintaining substantial conceptual connections between them. This pattern is important because specialization and integration are not necessarily opposing processes. The development of distinct thematic communities can indicate increasing maturity, while the persistence of connections between those communities indicates interdisciplinary integration. The resulting structure is therefore better interpreted as organized specialization rather than fragmentation. Previous studies have similarly identified the growing integration of artificial intelligence, adaptive learning, intelligent tutoring, and digital platforms within medical education (5, 6), while research on digital health interventions has emphasized the interaction between technological design, education, patient engagement, and healthcare delivery (8, 11, 12).

The comparison with previous literature also reveals an important distinction. Much of the existing literature examines particular technologies or educational applications separately, such as artificial intelligence, learning analytics, online learning, telemedicine, or digital health interventions. For example, reviews of AI in medical education have demonstrated expanding applications in clinical training, assessment, personalized learning, and skills development, while also emphasizing the need for stronger validation and appropriate educational integration. The present study contributes a different perspective by demonstrating how these apparently separate research streams are structurally related within a common knowledge network. The contribution is therefore not simply to show that AI or digital learning is important, but to reveal how educational, technological, and clinical concepts are becoming mutually connected within the intellectual architecture of the field. This interpretation is central to the WL-DHCM. The model should not be viewed as an independently imposed theoretical structure, but as a semantic synthesis of the empirical network evidence. Its principal contribution is to explain how the educational core, technological and informatics infrastructure, and clinical digital health applications interact within a common learning ecosystem. The model therefore provides a conceptual bridge between the empirical results and their practical meaning. The educational domain represents the pedagogical foundation, the technological domain provides analytical and intelligent capabilities, and the digital health domain connects learning with healthcare practice and patient centered applications. The model consequently shifts the interpretation of web based learning from an instructional technology perspective toward an ecosystem perspective. H3 provides the most important structural refinement of this interpretation.

The findings indicate that conceptual importance cannot be reduced to frequency or visual prominence. Closeness centrality identifies concepts that occupy relatively accessible positions within the overall network, whereas betweenness centrality highlights concepts that can connect otherwise differentiated areas of the knowledge structure. This distinction helps explain why concepts such as e learning, education, learning analytics, and performance can constitute part of the structural backbone, while artificial intelligence, semantic web, digital literacy, and telemedicine may acquire particular importance through their intermediary roles. The results therefore address RQ3 by demonstrating that centrality measures provide complementary information about the functional position of concepts within an interdisciplinary knowledge system.

The significance of these bridging concepts is particularly strong for medical education. Learning analytics can connect learner assessment with adaptive instruction and evidence informed educational decision making. Artificial intelligence connects computational methods with clinical reasoning, assessment, personalized learning, and healthcare applications. Digital literacy connects educational competence with the ability of health professionals to function effectively within increasingly digital clinical environments. Telemedicine connects formal learning with remote clinical practice and digitally mediated patient care. Thus, the importance of these concepts lies not only in their occurrence within the literature but in their potential to connect different knowledge communities. This interpretation is also consistent with evidence showing that AI is increasingly being considered across clinical education and healthcare, while concerns regarding validation, ethics, bias, and appropriate implementation remain unresolved. Taken together, the three hypotheses form a cumulative explanatory sequence rather than three independent findings. H1 identifies convergence among concepts. H2 explains how this convergence is organized into differentiated but interconnected thematic domains. H3 identifies the concepts that occupy structurally important positions within this organized system. The resulting sequence can therefore be interpreted as conceptual convergence, thematic organization, and strategic centrality. This progression strengthens the relationship between the research questions and the hypotheses. RQ1 is addressed by identifying dominant and influential concepts and their relationships. RQ2 is addressed by examining the organization and evolution of the conceptual network. RQ3 is addressed by identifying core and intermediary concepts through closeness and betweenness centrality. The WL-DHCM integrates these three levels into a single interpretation of the emerging digital health learning ecosystem. The educational implications are substantial. The results suggest that medical education should move beyond the simple incorporation of digital tools and toward the development of curricula that reflect the interconnected nature of contemporary healthcare knowledge. AI literacy, digital health literacy, learning analytics, telemedicine, data interpretation, and ethical use of intelligent systems should increasingly be considered as interconnected components of professional competence rather than isolated curriculum topics.

This direction is supported by previous evidence showing that formal AI education requires attention not only to technical knowledge but also to ethics, communication, collaboration, quality improvement, and professional attitudes (5). Recent evidence also suggests that digital education can improve knowledge and clinical behaviour, although the quality and certainty of evidence vary across educational modalities. The implications extend beyond curriculum design to clinical decision making and health policy. When learning, clinical evidence, patient information, and digital infrastructures become increasingly interconnected, medical education becomes part of the wider decision architecture of healthcare. The convergence identified in this study therefore has significance for how future clinicians acquire evidence, evaluate digital information, interpret analytic outputs, and interact with AI supported decision environments. The value of learning in digital health is consequently not restricted to improving educational outcomes. It can influence the capacity of health professionals to make informed decisions within complex, data rich healthcare systems. At the same time, this convergence makes ethical governance increasingly important because educational and clinical data may become interconnected, creating risks related to privacy, algorithmic bias, transparency, and unequal access.

These concerns are also emphasized in recent research on learning analytics and AI in medical education. From a policy perspective, the findings suggest that educational policy, digital health policy, and clinical innovation should not be developed as completely separate domains. The interdisciplinary structure identified in the network indicates that decisions concerning digital infrastructure, AI governance, health professional competencies, data literacy, and online education are increasingly interdependent. Consequently, policy makers and educational institutions need coordinated strategies that combine technological development with pedagogical quality, ethical governance, digital inclusion, and evidence based evaluation. This is particularly relevant because the benefits of digital education depend not only on technological availability but also on equitable access, appropriate educational design, and the capacity of users to engage meaningfully with digital systems. The broader literature similarly emphasizes the need to address the digital divide and to evaluate digital education within existing health professional curricula rather than treating it as a separate educational activity.

An important contribution of the present study is therefore the demonstration that convergence itself is a meaningful indicator of transformation. The emergence of a shared semantic space between medical education, intelligent technologies, and digital health suggests that the future development of the field will increasingly occur at their intersections. These intersections are precisely where the WL-DHCM places its bridging concepts. They represent potential sites for curriculum innovation, intelligent learning environments, clinical education, patient education, and evidence informed healthcare decision making. The model consequently provides not only a representation of the current knowledge structure but also a useful framework for identifying areas in which educational and technological innovation may have the greatest interdisciplinary relevance. Nevertheless, the findings should be interpreted within the limits of the analytical evidence. The semantic and structural patterns provide strong support for the proposed interpretations, but claims concerning changes in density or modularity should remain proportional to the quantitative metrics actually reported. Likewise, the WL-DHCM is an empirically grounded conceptual synthesis rather than a formally validated educational theory. Its value lies in integrating the complementary evidence from co occurrence, thematic organization, closeness, and betweenness into a coherent explanatory framework. Future studies should therefore test the model through longitudinal network analysis, expert evaluation, educational interventions, and empirical assessment of learning and clinical outcomes.

Overall, the discussion demonstrates that web based learning in digital health and medical education is increasingly developing as an interconnected knowledge ecosystem rather than as a collection of separate educational technologies. The convergence of pedagogical practices, intelligent technologies, learning analytics, and clinical applications creates new opportunities for medical education while simultaneously increasing the importance of ethical governance, digital competence, equity, and evidence based policy. The central implication of the study is that the future of medical education will depend not simply on adopting more digital technologies, but on understanding and managing the relationships among learning, data, technology, clinical practice, and healthcare decision making. The WL-DHCM provides a concise conceptual representation of this transition and positions web based learning as an important component of the emerging infrastructure through which knowledge is produced, interpreted, transferred, and ultimately applied in digital healthcare.

6. Conclusions

- Evolution of web-based learning into a digital educational ecosystem. Web-based learning has evolved from a model focused on content access and distribution into an integrated, data-driven learning environment supported by digital technologies—one closely linked to medical education and digital health.
- Integration of emerging technologies into educational processes. Education remains the structural core of the field, yet it increasingly incorporates learning analytics, artificial intelligence, machine learning, and digital literacy. These technologies expand the possibilities for assessment, feedback, personalization, and adaptive learning without replacing traditional educational foundations.
- Convergence of medical education, technology, and clinical practice. The growing connection between medical education, telemedicine, digital health, and healthcare applications demonstrates that learning extends beyond the classroom and integrates into real-world healthcare settings. The goal is no longer merely to acquire knowledge, but to develop the competencies needed to navigate digitized healthcare systems.
- Implications for research and the future of medical education. Findings point to an interdisciplinary transformation rather than a simple expansion of online education. The future of web-based learning will depend on the ability to coherently integrate educational knowledge, digital technologies, and healthcare practice—highlighting priority areas for research, scientific investment, and interdisciplinary collaboration.

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