The Path to Comprehensiveness: An LLM-Enhanced Systematic Literature Review on the Innovation Mindset

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Abstract

The study of the innovation mindset is not new, either within business and management or beyond. However, most existing studies and meta-analyses rely on manual coding or simple keyword filters, which may overlook important artifacts given the vast scope of the task. In this work, we try to overcome the comprehensiveness problem by introducing a multi-LLM ensemble pipeline that integrates DeepSeekR1, Llama3, and QWEN models to retrieve, classify, and thematically cluster scholarly articles. Applying the pipeline to 106 peer-reviewed publications, we identify four recurrent themes: (A) Creativity-Risk Synergy, (B) Innovation Capacity, (C) Entrepreneurial Orientation, and (D) Adaptability and Problem Solving. These combinations improve over author-supplied keywords, demonstrating the methodological value of using LLM models. The identified themes clarify the key needs for further research into the innovation mindset and offer an agenda for future explorations in information systems sciences.

Keywords: Innovation Mindset, Systematic Literature Review, Large Language Models, Thematic Clustering, Meta-Analysis.

1. Introduction and Background

The innovation mindset has emerged as a focal construct across management, education, and policy scholarship, and the topic has been amply studied. Despite its frequent study and common usage, the conceptual definition and boundaries remain fuzzy, particularly in relation to other well-established constructs such as the entrepreneurial mindset. In the educational context, the innovation mindset is defined as a set of beliefs and attitudes that lead to developing the capacity to produce valuable novelty (Konak et al., 2025). Some studies clearly overlap the concepts, while others confine the entrepreneurial mindset to individual-level traits (see (Naumann, 2017) for a review) while expanding the innovation mindset to broader organizational levels and cultures.

We suspect that this conceptual fuzziness surrounding the concept of innovation mindset and its derivatives, the entrepreneurial mindset, stalls both theorizing and application. Extant scholarship also lacks a coherent definition and operationalization of an innovation mindset distinct from an entrepreneurial mindset. Therefore, we set out to conduct an extensive review of studies using a comprehensive methodological approach to ground key thematic areas for further research. Defining an innovation mindset is important as it helps design new assessment instruments and generates new (derivative) knowledge.

We present a systematic literature review (SLR) that leverages large language models (LLMs) to map, synthesize, and critically evaluate how researchers define, operationalize, and measure the "innovation mindset." An SLR is one way of developing a theoretical definition of constructs and their operationalization. SLRs rely on precisely retrieving and coding large, diverse bibliographic datasets. However, metadata are often incomplete, keywords are non-specific, and topic boundaries (such as "innovation mindset" versus "entrepreneurial mindset" versus "entrepreneurial orientation") are only implicitly signaled. LLMs can help overcome these challenges by conducting semantic screening and extracting concepts beyond simple keyword matches, inferring missing descriptors, clustering related studies, and quickly filtering out irrelevant records.

In this paper, we propose and test a methodology for creating bibliometric maps from SLR using LLMs. By utilizing LLM-assisted thematic coding and analysis, we aim to uncover theoretical backgrounds, cognitive and affective components, and contextual factors that shape research on the innovation mindset. Unlike traditional methods constrained by fixed metadata fields, LLMs can analyze literature from

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multiple interpretive perspectives. For example, they enable categorization and comparison based on application domains, theoretical frameworks, methodological paradigms, or even the implicit epistemic stance of a paper. This flexibility not only supports the depth of analysis but also allows for the inclusion of underrepresented concepts, such as an innovation mindset that may have been inconsistently labeled or sparsely indexed in literature databases or might have created gaps in review, given the limited manual replicability and scalability constraints.

This study addresses this gap in manual coding by leveraging the advantages offered by LLMs. While this paper builds on a substantial traditional literature review that summarizes essential studies in the field, its primary contribution lies in the methodological approach to systematically reviewing scholarly work. Papers from the literature were selected to answer our key research question, "*What are the core attributes and characteristics of an innovation mindset as conceptualized across academic literature*?" The traditional literature review helped us frame our methodological work, validated the need for it, and provided a benchmark of key thematic areas against which we reviewed the LLM-driven results. The LLM-review makes two contributions: (1) it presents an ensemble SLR studies pipeline and evaluates its performance against (our) human benchmarks; and (2) it applies the pipeline to the innovation-mindset corpus, revealing a concise thematic structure that reconciles prior conceptual fragmentation.

2. Traditional Literature Review of Innovation Mindset

Due to space limitations, this section provides a condensed summary of the traditional literature on the innovation mindset. The findings are organized into four categories—organizational, personal, global, and teachability—each emphasizing distinct yet interconnected dimensions that influence how innovation mindsets arise and can be nurtured.

Organizational Level Attributes: Organizational research frames the innovation mindset as a foundational driver of sustained growth, shaped by culture, leadership, and structural processes. Kuczmarski (1998; 1996) argues that innovation thrives in cultures that welcome failure, promote cross-functional collaboration, and institutionalize structured development strategies. Kahn (2018) emphasizes embedding innovation principles—questioning, experimenting, empathy—across all levels to create a culture that embraces ambiguity and iterative learning. Trust emerges as a central enabler in open innovation, facilitating knowledge-sharing and ambidextrous thinking (Salampasis et al., 2014). Leaders must adopt a mindset of strategic agility, balancing exploration and execution amid global uncertainty (Cassiman, 2015). Studies in education and healthcare (El-Sayed et al., 2025; Özdemir et al., 2024) confirm the transferability of this mindset, showing how institutional openness empowers teachers and nurses to adapt and innovate. An open innovation mindset, as defined by Gomezel and Rangus (2018), links collaboration and alertness to measurable organizational success.

Personal Level Attributes: Personal perspectives on the innovation mindset highlight it as a collection of teachable, measurable psychological traits and cognitive orientations. McLaughlin et al. McLaughlin and McLaughlin (2021) argue against the myth of innate creativity, proposing that structured ideation can be learned as a skill. The Berkeley Innovation Index (BII) (Sidhu et al., 2016) operationalizes core traits—trust, resilience, belief, and collaboration—demonstrating measurable growth through guided training. Studies using the BII show individual variation: SME owners prioritize belief and caution, while startup founders depend on resilience and experimentation (Fitri & Pertiwi, 2019; Harsono & Fitri, 2020). Other research conceptualizes innovation as a sequence of mindsets—curiosity, creativity, and clarity—that guide behavior through problem-solving phases (Walsh et al., 2022). Alwi et al. (2018) link traits like diversity and perfectionism to innovative behavior. Similarly, Maziriri et al. (2024) find that innovation conviction and mindset significantly shape entrepreneurial success, especially among women. Together, these studies confirm that innovation is grounded in dispositions and attitudes shaped by experience, beliefs, and education.

Global perspectives attributes: The global innovation mindset is a cultivated cognitive ability grounded in cross-cultural awareness, strategic agility, and interdisciplinary collaboration. It enables leaders, particularly in SMEs, to recognize and act on international opportunities through innovation (Kyvik, 2018). This mindset connects innovation, entrepreneurship, and internationalization, influenced by global exposure and education (Felício et al., 2016). It also manages global-local tensions and drives innovative behavior under resource constraints (Levy et al., 2007), making it critical for effective global engagement.

Teachability: Research consistently demonstrates that the innovation mindset is teachable through structured environments and experiential learning. Training models such as boot camps (Skaggs et al., 2012) and academic ecosystems (Nagel et al., 2020) cultivate traits like curiosity, collaboration, and resilience. Innovation competitions and programs (ICPs) also shape self-awareness and open-mindedness

(Kulturel-Konak & Konak, 2025), while enhancing problem-solving, teamwork, and impact thinking. Frameworks like KEEN's Entrepreneurial-Minded Learning (EML) and 3Cs (curiosity, connections, creating value) integrate an entrepreneurial mindset into innovation education (Konak et al., 2025). These approaches validate innovation as a developable capacity in college settings, not innate talent. Building on these insights, our next step was to develop an LLM-enabled methodology to systematize and extend the review

3. Systematic Literature Review Using LLMs

A systematic literature review (SLR) involves a rigorous methodical approach to identify, evaluate, and synthesize all relevant research on a specific topic. SLRs indicate areas where knowledge is insufficient or further investigation is required. In recent years, bibliometric maps, popularized by software tools such as VOSviewer, have become a frequent method for presenting the results of SLRs. These tools allow researchers to visualize bibliometric maps, which display relationships between publications, authors, keywords, or journals. This visual mapping helps researchers identify clusters of related concepts (e.g., subfields, themes, or research topics as well as gaps) and see how concepts are interrelated or distinct.

SLR requires large datasets that are carefully cleaned and formatted. Unfortunately, citations may include non-standard or incomplete metadata. One challenge is that the paper's keywords or abstracts may be missing items or may not accurately represent the content citations. Such problems complicate analysis and already-challenging SLR processes. We faced these problems while mapping the concepts related to "innovation mindset." First, the number of papers focusing on an innovative mindset is limited, and their keywords lack specificity, making it difficult to compare this concept with adjacent topics. This presents a challenge when mapping concepts. LLMs are increasingly used to automate and enhance systematic literature reviews, such as screening titles and abstracts, and extracting key concepts (Joos et al., 2024; Khraisha et al., 2024; Susnjak et al., 2025). For example, LLAsist (Haryanto, 2024) relies on user-generated questions to evaluate the relevance of the literature, aiming to reduce time and increase accuracy. LitLLM (Agarwal et al., 2024) employs Retrieval-Augmented Generation (RAG) to combine LLMs with web search and re-ranking mechanisms. This approach retrieves and summarizes the most relevant literature to reduce hallucinations and enhance the quality of generated reviews. There are also several AI-based tools to support SLR. For example, Semantic Scholar, ResearchRabbit, Iris.AI help with paper discovery and analysis. Elicit and Consensus help with synthesis and analysis. DistillerSR claims to automate all stages of an SLR.

3.1. Methodology

Our proposed methodology is made up of three independent modules: 1) Theme Extraction Module, 2) Theme Construction Module, and 3) Export Module (as shown in Figure 1). Each module can be run independently. For example, the corpus can be sent to the Theme Consolidation Module. Different types of LLMs are used in various stages.

1) Theme Extraction Module: The theme extraction module analyzes academic papers and summarizes the key concepts as keywords. Each paper is first parsed using a PDF reader, and the extracted text is fed into an LLM, which is instructed to return a Python dictionary with keys representing attributes/themes and values corresponding to contextual summaries. The prompt is thoughtfully designed at both the system and user levels. The system-level prompt instructs the LLM to behave as an academic assistant and extract only those themes that truly appear in the document, without inventing new attributes. The user-level prompt gives the LLM tasks to perform and specifies the data structure it should return. It can also be customized to match the study's goal. For instance, the LLM can be directed to focus on personal traits, organizational structures, or the paper's context. In this study, the emphasis is on broader themes. All models are run locally to prevent copyrighted manuscripts from being uploaded to public LLMs.

The process is repeated using different LLMs as parallel annotators, each making their key-definition extraction from each paper independently. In the next stage, these independently and parallelly generated key-definition dictionaries—one from each base model—are input into another LLM to produce a unified consensus vocabulary for each paper. In this stage, an LLM is instructed to detect semantically equivalent themes for each paper across the independent LLMs, choose a succinct label representing the meaning while staying true to the original labels, and synthesize a merged definition that integrates evidence from all LLMs. This process yields a Python dictionary of keywords based on the consensus of the other LLMs.

2) Theme Consolidation Module: This module reduces the number of keys representing the concepts extracted by the LLM module. When an LLM is asked to extract key-definition pairs from academic papers, it typically returns many near synonyms, such as "Mind-Set Shift," "Paradigm Change," and "Mindset Shift." This theme reduction module aims to consolidate this noisy vocabulary into a concise, non-redundant theme list. If the number of keys is relatively small, the process can be completed manually or omitted. The outcome of this process is a thesaurus file that maps the original keys to their synonyms. We have implemented a two-stage process to achieve this outcome. In the first stage, keys are encoded into fixed-dimensional vectors using a pre-trained embedding model. These embedding models tend to preserve semantics by mapping similar meanings into closer vectors and dissimilar ones into more distant vectors. In the following steps, the embeddings were L_2-normalized, and a clustering algorithm groups these vectors into clusters, thereby reducing the size of the original key set. In the next stage, an LLM analyzes the key concepts in each identified cluster and determines a label that represents that cluster.

3) Export Module: This module updates the keywords of the original corpus and creates a new Research Information System (RIS) file, a standardized text-based format for bibliographic citation data, to be analyzed in literature analysis software such as VOSView.

3.2. Procedure

We conducted a systematic literature search using the terms "innovation mindset," "innovative mindset," and "innovative thinking" across the Web of Science and Scopus databases, targeting journal papers and conference proceedings. The initial search yielded over 200 publications, which were subsequently refined to 138 relevant papers through author screening. Access to full-text PDFs was obtained for 106 papers, forming the final corpus for analysis.

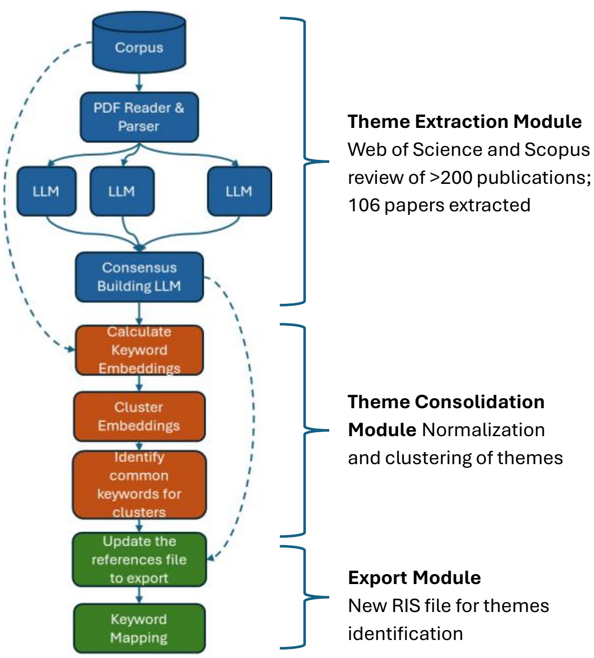

Figure 1. The proposed approach of using LLMs for the SLR.

LLM Prompts Definition: The corpus of PDF files (after extracting their text content) was analyzed to identify and categorize themes related explicitly to "innovative mindset" or "innovation mindset" within each document. We employed a two-level prompting strategy, utilizing distinct system and user prompts. The system prompt acts as a meta-instruction that defines the LLM's role and behavioral constraints as follows: *"You are an academic assistant. Extract only those themes that truly appear in the document; do not invent new attributes."* The user prompts include the specific task instructions and actual content to be analyzed as follows "*Read the following document and identify any sections or themes that relate to an 'innovative mindset' or 'innovation mindset'. Look for indicators and attributes that the paper connects them to innovative and innovation mindset. Summarize them with references to their context if possible. In the results, summarize these as a Python dictionary named `themes`. Each key in the dictionary should be an attribute or theme, and the value should be a short summary explaining the context in which it appears in the paper*." The LLM returns findings as a Python dictionary. We prompted the LLM independently for each paper and repeated this process using DeepSeek-R1, LLama3, and QWEN3, with a temperature parameter of 0.2 to reduce randomness. The outputs of the three LLMs are stored in separate files.

Semantic Screening & Standardization: Next, we implemented a multi-model consensus approach for identifying innovation mindset themes across three different LLMs. For each paper, the keyword dictionaries from three LLM analyses are compared using a fourth LLM (LLaMA3) acting as a "consensus judge." This meta-LLM is instructed to identify overlapping concepts across the three sources, resolve semantic duplicates (e.g., "Mind-set Shift" vs. "Paradigm Shift"), and create canonical representations. The consensus process enforces strict formatting constraints: atomic keywords (≤3 words in Title Case), merged academic definitions (≤40 words), and pure JSON output without markdown or commentary. The system and user prompts are too lengthy to be included in this paper, due to space limitations. However, they prioritize conceptual unity while maintaining fidelity to the original thematic labels. The result is a paper-level consensus dataset, where each document has a unified set of innovation mindset keywords representing the collective judgment of all three LLMs, thereby reducing individual model biases through ensemble agreement. We also created a new RIS file of the papers by updating their keywords with the extracted ones so that the keyword map can be plotted in VOSViewer.

Dimensionality Reduction: In the next step, we applied the theme consolidation module to reduce the number of keywords by mapping similar ones to higher-level concepts. First, we generated keyword embeddings using the mxbai-embed-large model, a specialized LLM designed for creating high-quality vector representations of text and optimized for semantic similarity tasks, which produces dense vector embeddings that capture the contextual meaning of input terms. Agglomerative hierarchical clustering is applied to keyword embeddings using cosine similarity and average linkage to organize the data into 200 distinct clusters, with each keyword assigned a cluster ID. Llama3 LLM is employed to automatically generate concise academic theme names for each cluster by analyzing the constituent keywords and selecting the most representative term within a three-word limit. We mapped generated theme names to their respective clusters, and this file is used as a thesaurus file. All analyses were performed locally on a Mac (M3 Max, 48GB RAM, 30 GPU cores) running LLMs as a service, allowing us to keep the copyright-protected material local.

4. Results

Figure 2 illustrates the "raw" keyword co-occurrence map that was generated directly from author-supplied keywords in the 106 papers extracted. This map is based on 55 keywords that appear more than once in a total of 436 unique keywords. Authors overwhelmingly frame their work around the generic term "innovation," as it dominates the keyword map. Using the color-coding scheme, we see that strong blue links connect "innovation" to technical implementations ("digital innovation," "integration," "artificial intelligence") and barriers ("implementation," "user acceptance," and "strategy"), suggesting that papers often discuss both the technology and its adoption challenges in the same breath. In the red cluster, keywords such as "dynamic capabilities," "open innovation mindset," "transformational leadership," "HRM practices," and "leader–member exchange" indicate that authors lean on the dynamic-capability literature to explain organizational antecedents of innovation mindset. In the yellow cluster, keywords such as "education," "knowledge," "entrepreneurship," and "thinking" come together, revealing a teaching-oriented subset that talks about mindset in cognitive or pedagogical terms rather than organizational ones.

Overall, it is challenging to interpret the raw keyword map in Figure 2 for several reasons. Firstly, generic single-word keywords like "model," "technology," and "knowledge" attract many co-links but convey little conceptual meaning. This affects the centrality of the network map without providing insight. Secondly, the "innovation mindset" appears as an isolated node, despite being conceptually core to our study (note that "innovation mindset" was used as the search term). This observation shows that relying solely on author keywords misses latent meaning. Thirdly, we observe an amalgamation of concepts. For example, keywords "performance" and "implementation" appear in the same red sub-cluster as "dynamic capabilities," blending antecedents with outcomes. The author's raw keywords are very broad and have high redundancy, although they can provide some insight (e.g., realizing organizational structures and support). One reason for this is that many keywords have similar or close meanings, but they were removed because they only appear once. Hence, the raw usage of keywords leads to maps that are difficult to interpret. To address this issue, we utilized the theme reduction module on the author keywords to determine if it could generate maps that would provide better insights, as illustrated in Figure 3.

Figure 3 illustrates the resulting raw-keyword map after applying the theme reduction module on the keywords. This time, the map includes 71 keywords. Compared to Figure 2, a larger and more connected map was obtained because the theme reduction module increases the number of repeating keys by mapping similar words into broader keyword themes. In the theme reduction module, the number of clusters was 220. This map is useful for an overall view of topical breadth. The keyword "innovation," which is the central node in the red cluster, is strongly connected to keywords: "digital transformation," "human resource management," "human capital development," "evaluation methodology," and "AI capability," suggesting the technology-centric and organizational capability of innovation. The keyword "innovation mindset" is not orphaned in Figure 3. It is central in the green cluster and strongly connected to "innovation," "social impact assessment," "innovation ecosystem," and "ambidexterity." This cluster associates "innovative mindset" with psychological and ecosystem factors. The yellow cluster includes keywords related to human resources management and organizational processes, such as "job satisfaction," "process management," "professional development," and "market segmentation theory," bringing innovation and indicating an operational focus. Although the map in Figure 3 has fewer orphan nodes, it is challenging to identify patterns due to the overlap of many cluster boundaries. The resulting keyword map lacks the information to answer our research questions.

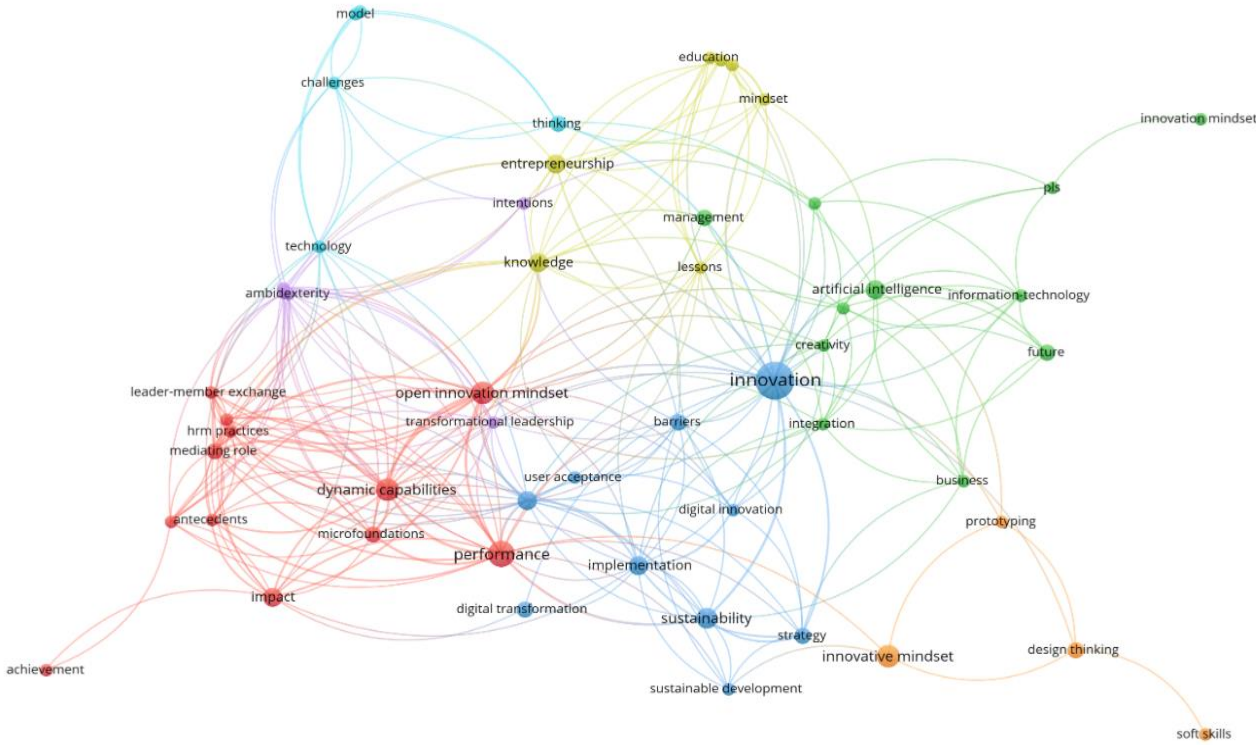

Figure 2. The keyword map based on the original paper keywords without theme consolidation.

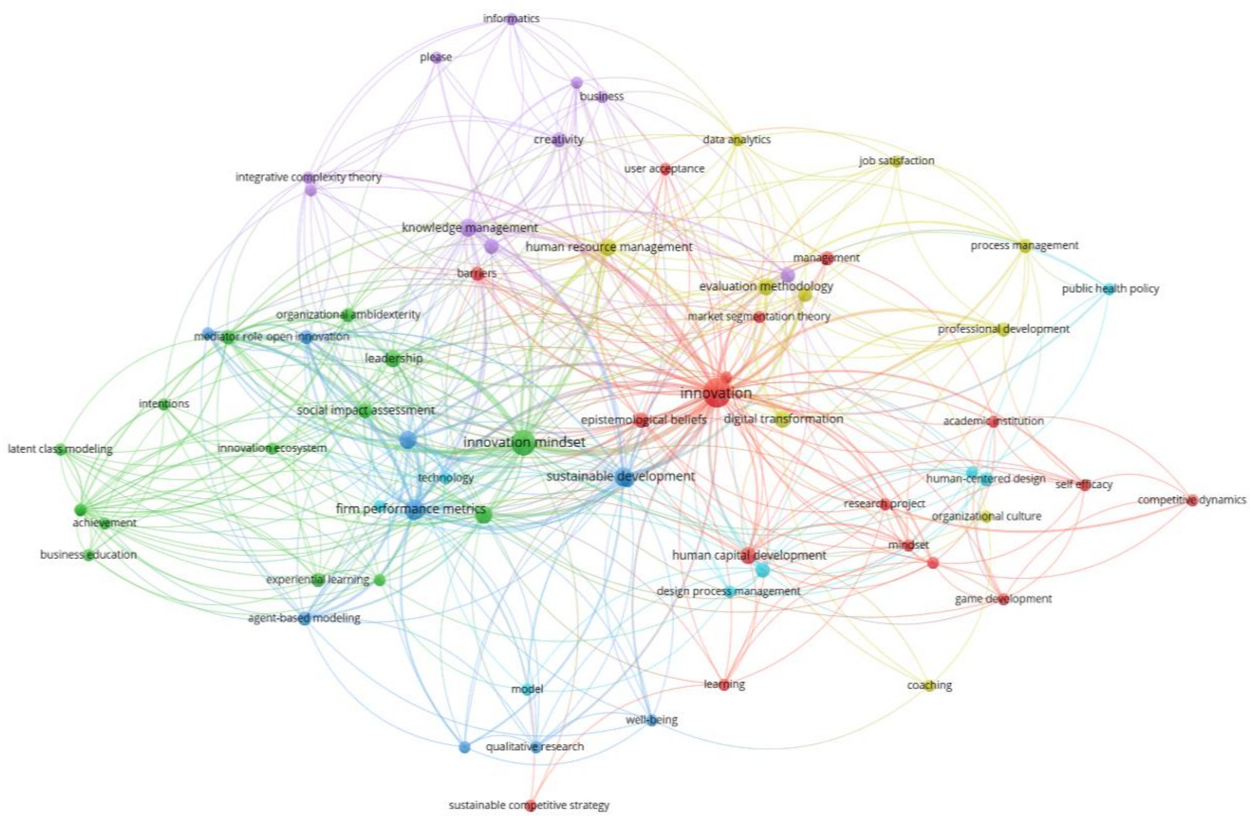

Figure 3. The keyword map based on the original paper keywords with theme consolidation.

Figures 4 and 5 illustrate the keyword map obtained by consensus among the three LLM models (DeepSeekR1, LLAMA3, and QWEN3), which was subsequently processed through the theme consolidation process. In Figure 4, since the theme consolidation module does not process the keywords, terms "innovation mindset," "mindset shift," and "innovative mindset" appear independently. Although the map was not cleaned using a thesaurus, it clearly provides information related to our core research question. The details of the clusters will be discussed for Figure 5, but not for Figure 4, due to the brevity of the paper. However, the analysis using LLMs reveals that the innovation mindset is not considered a static trait, but rather a developmental pathway (i.e., a mindset shift) in the literature. Now, concepts such as creativity, adaptability, social scaffolding, collaboration, and risk-taking appear in the maps. These concepts are crucial for our research questions but are absent from the earlier maps. While the earlier analysis based on paper keywords focuses on organizational constructs and structures, our LLM-based analysis shows scholars are extrapolating the individual shift narrative to meso- and macro-levels (teams, organizations). This observation is consistent with our traditional review literature.

In Figure 5, the keyword "innovation mindset" is at the center of the network and is densely connected to other nodes. This is a result of combining multiple terms related to "innovation mindset." The clusters in the figure are more distinct and relevant to the objectives of the analysis. The larger, core clusters are:

(A) Red cluster— Creativity and Risk— The keywords include "creativity," "divergent thinking," "risk appetite," "openness to experience," and "open-mindedness," which form a dense group. These keywords suggest that the willingness to experiment under uncertainty is viewed as a fundamental emotional component of an innovative mindset.

(B) Lime/Blue cluster— Innovation Capacity— The keywords include "innovation capacity," "resilience," "interdisciplinary collaboration," "learning," "perfection," and "trustworthiness." These keywords are also connected to the blue cluster: "leadership," "commitment," "failure learning," "employee engagement," and "uncertainty embracing." Based on insights from the literature review, these findings suggest that innovation capacity is not acquired in isolation, but rather through interdisciplinary collaboration. The role of leadership commitment is evident in this cluster.

(C) Green— Entrepreneurial Orientation— The keywords include "entrepreneurial mindset," "growth mindset," "open innovation mindset," "innovation strategy," "design thinking," "human-centered design," "open-innovation mindset," and "transformational leadership." This group is strongly associated with the keywords in the Lime/Blue Cluster, including "innovation capacity" and "interdisciplinary collaboration." These clusters suggest that opportunity-seeking orientations complement pure creativity, broadening the innovation mindset to include strategic perspectives.

(D) Purple— Adaptability and Problem Solving—These two keywords are highlighted and directly relate to the innovation mindset.

Several peripheral clusters have distinct meanings. The teal-colored cluster includes keywords such as "problem-based learning," "real-world experience," and "entrepreneurial education," highlighting the role of experiential learning in developing an innovation mindset. The keywords such as "life-long learning" also support the role of education. The sparsely connected outliers ("global mindset," "cognitive complexity," "intuitive process," and "problem-solving skills") suggest that the map in Figure 5 can benefit from more theme consolidation to reach a stronger definitional consensus of the concepts. The map illustrates the innovation mindset as a multidimensional concept combining cognitive flexibility, creative risk-taking, resilience-based learning, entrepreneurial strategy, and collaboration. Each color-coded cluster represents a connected aspect of this broader psychological and organizational skill.

5. Discussions

As we discussed in the introduction and literature review sections, the innovation mindset has been overly studied, but it has been difficult to pin down because it encompasses many other concepts (such as the entrepreneurial mindset) and many different fields. Conceptual overlaps are plentiful, many of which are revealed through our traditional (human-driven) literature review presented in the Background section. Some studies consider the innovation mindset to be an individual disposition, while others integrate it into organizational culture. This multi-level application of the term was noted in our traditional literature review and the analysis using LLMs. Based on our traditional literature review and LLM-driven analysis, we addressed the following question: "***What are the core attributes and characteristics of an innovation mindset as conceptualized across academic literature?***" We can define the innovation mindset as a teachable belief system that couples creative risk-taking with adaptive learning behaviors and trust-based collaboration to generate valuable novelty across individual and organizational contexts.

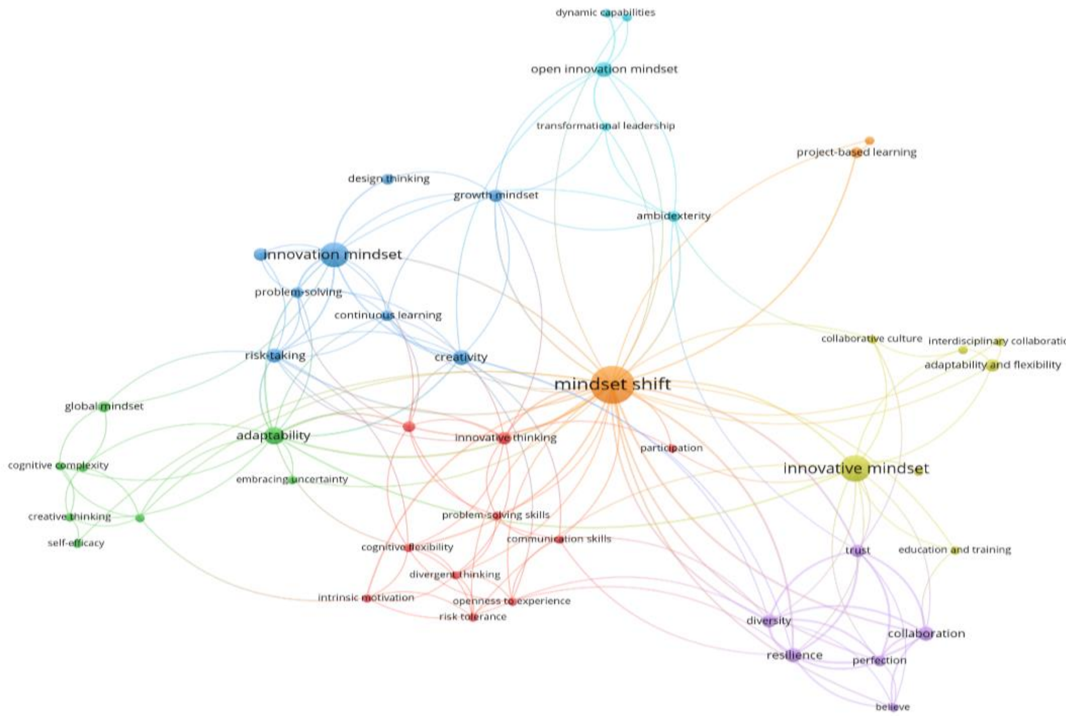

Figure 4. The keyword map based on keywords obtained by the theme extraction module without theme consolidation.

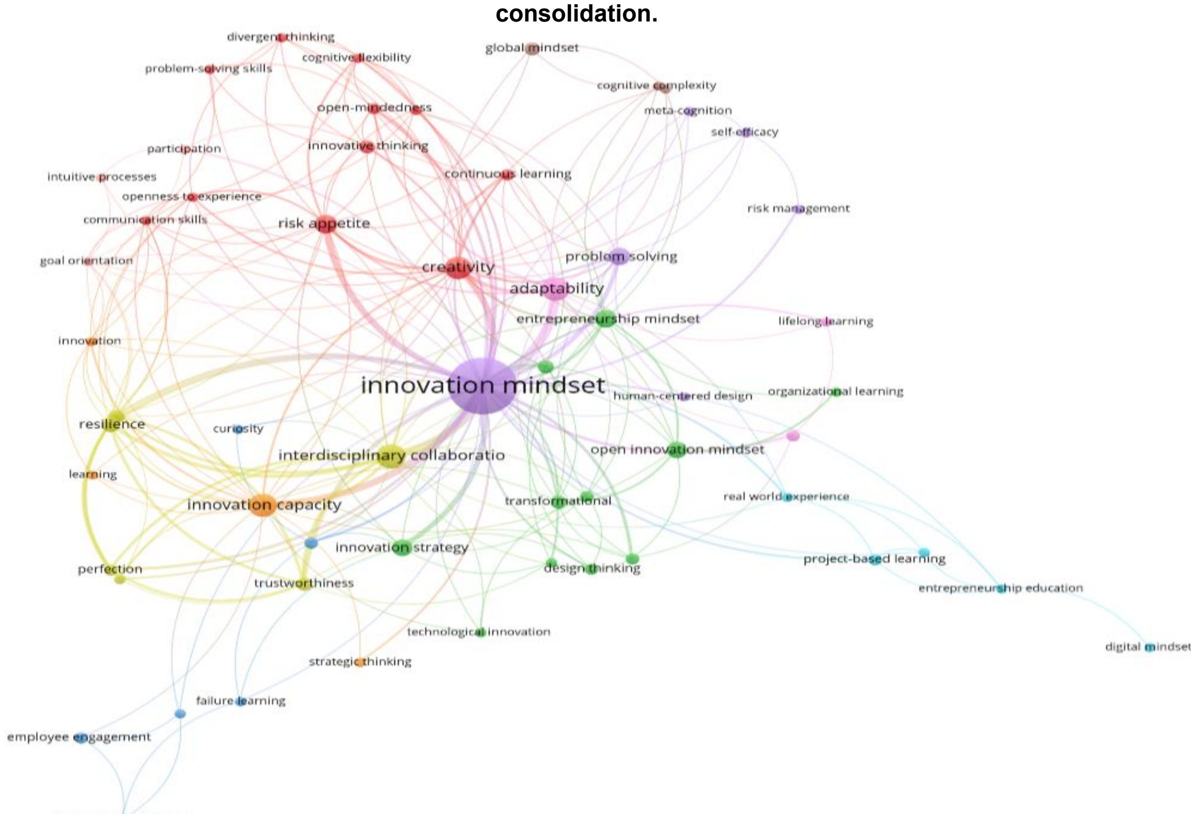

Figure 5. The keyword map based on keywords obtained by the theme extraction module with theme consolidation.

These dimensions emerge as the most densely interconnected nodes around the innovation mindset in Figure 5 (gold, red, blue clusters) and echo traits reported in the literature (trust, resilience, collaboration).

The themes and keywords uncovered by a manual traditional literature search were:

- **Organizational level attributes** – failure welcome, strategy processes institutionalized, culture that appreciates ambiguity, trust, and ambidexterity
- **Individual level attributes/personality traits** – teachable skills, measurable, belief-based, optimistic, curiosity, and creativity
- **Global perspectives attributes** – engagement in cross-border collaboration, exposure to international education, and stresses local and global tensions
- **Teachability** – mindset can be developed through growth expectations for all, bootcamps can help develop, and an academic ecosystem supports mindset construction.

In contrast, the themes and keywords uncovered by the LLM-SLR presented in this paper were:

A. **Creativity and Risk** – risk taking, divergent thinking, experimentation
B. **Innovation Capacity** – continuous learning, reflection, growth mindset, trustworthiness
C. **Entrepreneurial Orientation** – design thinking, human-centered design, transformational leadership
D. **Adaptability and Problem Solving** – meta-cognition, cognitive complexity, open innovation, global mindset.

By linking the thematic areas identified in the traditional literature review with those clustered and extrapolated in the LLM model, we find areas of overlap (A and B) but also significant divergence (C and D). For example, the extant literature broadly differentiates between firm-level and individual attributes, but the LLM-SLR did not identify these dimensional differences. Risk propensity and psychological behaviors of leaders may, in fact, be precursors to firm-level culture. One can look at Apple, Tesla, and Microsoft-IBM to relate the importance and interconnection of individual founders and organizational discipline development. Likewise, the growth mindset of organizations can easily parallel individual growth mindset, and the question for innovation is not if, but rather how to measure this orientation in firms (as opposed to individuals).

Regarding divergence, while we know from the literature review that there is a difference between entrepreneurial and innovation mindsets, at least in terms of scope, this was not particularly relevant in the literature identified in the LLM analysis. This may mean that our differentiation among those fields is overinflated, and they may be more connected when our research domain expands to other areas than strict management literature. Finally, while the traditional literature focuses much on teachability especially through the higher education system description of successful entrepreneurial ventures, the LLM-SLR focused more on concepts of complexity, adaptability and metacognition as prerequisites for innovation development, with cognitive complexity requiring that capabilities may be already acquired or needed at the organizational level to push innovation further (as opposed to being developed like in a higher education environment).

One limitation of the research is the limited number of papers analyzed (only 106 PDF-accessible papers). The same team co-authored some of these papers and, therefore, focused on similar concepts, which can introduce bias into the analysis. The LLM ensemble approach reduces hallucinations, but it does not entirely eliminate them. Especially in the theme consolidation module, the authors required a manual check, as some of the mapping was found to be irrelevant. Another limitation is that the computational resources required for this analysis were a concern. The analysis highly depended on the availability of the GPU on the local computer. Due to limited memory, we were only able to run models that require no more than 32 GB of memory, and the tasks took several days to complete. This hinders the replication of results and may compromise the long-term validity of the findings if replication cannot be achieved promptly using the same instructions across systems with varying capacities and processing capabilities.

5. Conclusions

This study presents a proof-of-concept LLM-SLR pipeline that significantly improves upon traditional methods and reveals a coherent four-theme structure of innovation mindset research, surpassing self-selected keywords and summary analyses that are challenging to scale. The methodological approach fosters advancement and presents conclusions that are both convergent and divergent from existing literature, thus providing an additional avenue for further research into the characteristics and evolution of innovation mindsets. This scalability and comprehensiveness, leading to reliable results and new insights, promise future applications.

Future research should include a larger and more diverse set of papers, utilize more advanced computational resources to enhance replicability, and investigate how innovation and entrepreneurial mindsets evolve across different contexts.

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