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Research article

The intellectual structure of learning agility: A case study using a modified BERT model for topic modeling

La estructura intelectual de la agilidad del aprendizaje: Un estudio de caso utilizando un modelo BERT modificado para el modelado de temas

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Abstract
Introduction: The study aims to deepen the understanding of learning agility, a relatively new construct in the field. Learning agility is essential for identifying and developing leadership talent in organizations, particularly in environments of constant change. **Methodology:** A thematic analysis was conducted on the titles and abstracts of 112 significant works on learning agility. The analysis utilized abstract clustering and a modified version of the BERT model for topic modeling. These influential works were identified through a prior study using bibliometric citation techniques. **Results:** Nine intellectual topics or patterns related to

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learning agility were identified, along with the influential works within each topic. The results were then compared to another intellectual structure derived from a co-citation analysis of the same set of works. Correspondences between the topics identified through both methods were established. **Discussion:** The comparison between topics identified through thematic analysis and co-citation analysis provides a comprehensive perspective. This integrated approach helps to advance towards a unified conceptualization of learning agility, which is essential for standardizing its measurement and application. **Conclusions:** The study demonstrates that combining bibliometric techniques and Natural Language Processing (NLP) facilitates academic exploration in complex research areas. This approach enables the development of more objective and reliable tools for organizations to identify and develop leadership talent.

Keywords: learning agility; intellectual structure; topic modeling; BERT; leadership; potential; identification; development.

Resumen
Introducción: El estudio pretende profundizar en la comprensión de la agilidad del aprendizaje, un constructo relativamente nuevo en este campo. La agilidad en el aprendizaje es esencial para identificar y desarrollar el talento de liderazgo en las organizaciones, especialmente en entornos de cambio constante. **Metodología:** Se realizó un análisis temático de los títulos y resúmenes de 112 trabajos significativos sobre la agilidad del aprendizaje. El análisis utilizó la agrupación de resúmenes y una versión modificada del modelo BERT para el modelado de temas. Estos trabajos influyentes se identificaron mediante un estudio previo en el que se utilizaron técnicas bibliométricas de citas. **Resultados:** Se identificaron nueve temas o patrones intelectuales relacionados con la agilidad en el aprendizaje, junto con las obras influyentes dentro de cada tema. A continuación, los resultados se compararon con otra estructura intelectual derivada de un análisis de co-citación del mismo conjunto de obras. Se establecieron correspondencias entre los temas identificados mediante ambos métodos. **Discusión:** La comparación entre los temas identificados mediante el análisis temático y el análisis de co-citación proporciona una perspectiva global. Este enfoque integrado ayuda a avanzar hacia una conceptualización unificada de la agilidad del aprendizaje, esencial para estandarizar su medición y aplicación. **Conclusiones:** El estudio demuestra que la combinación de técnicas bibliométricas y de Procesamiento del Lenguaje Natural (PLN) facilita la exploración académica en áreas de investigación complejas. Este enfoque permite desarrollar herramientas más objetivas y fiables para que las organizaciones identifiquen y desarrollen el talento de liderazgo.

Palabras clave: agilidad de aprendizaje; estructura intelectual; modelado de temas; BERT; liderazgo; potencial; identificación; desarrollo.

1. Introduction

In this context of change and disruption, where organizations must continually and rapidly adapt, leaders must not only learn from their new professional experiences upon promotion but also continue to learn in their current positions. This necessity arises from the obsolescence of existing skills and the emergence of new ones that enhance job efficiency.

As a result, Michael Lombardo and Robert Eichinger first coined the concept of learning agility in 2000 to identify potential talent and develop leadership. The concept was defined as "the willingness and ability to learn from experiences and subsequently apply that learning to perform under first-time, tough or different conditions" (Lombardo & Eichinger, 2000, p. 2).

Learning agility is praised by HR practitioners for its effectiveness in identifying talent and developing leaders. However, the academic community has only recently begun to explore this concept, leading to a lack of consensus on its definition and measurement. Many theoretical questions remain unexplored, and much empirical research has yet to be conducted. This lack of agreement has hindered progress both theoretically and empirically, impacting its application in other fields like education.

Therefore, to partially address this gap, it is necessary to gain a deeper understanding and provide a global perspective on this relatively new construct. This will equip future academics, practitioners, and educators with the insights required to develop new theories (Ritzer et al., 2001) that help reach a consensus on its definition and unify its conceptualization, thereby standardizing its measurement and development.

To address this issue as part of a broader meta-theoretical investigation, "In search of an integrative conceptualization of learning agility", this new study, "The intellectual structure of learning agility: A case study using a modified BERT model for topic modeling", intends to:

1) Explore the 112 most influential abstracts on learning agility, according to Grau-Garca et al. (2024)[2], those that have made the most significant impact on this field thus far.

2) Group the abstracts based on their similar characteristics or shared patterns.

3) Identify and interpret the topics of each cluster.

4) Empirically map the abstracts on a two-dimensional space.

5) Compare and evaluate Natural Language Processing ("NLP") techniques employed in this study with the bibliometric techniques of co-citation used previously in a different study by Grau-Garcia et al. (2024) to identify the different lines of knowledge and research within the construct of learning agility, for the same dataset of documents.

In any case, this study aims to substitute extensive reading and fine-grained content analysis. To achieve this objective, a thematic analysis was conducted on the titles and abstracts of the 112 most significant scientific works on learning agility (Grau-Garcia et al., 2024), utilizing abstract clustering and a modified version of the BERT model for topic modeling.

To the best of our knowledge, this need has never been methodologically addressed by topic modeling, a technique employed in "NLP." Instead, it has been approached through extensive narrative literature reviews and meta-analyses of the construct (e.g., De Meuse et al., 2017; DeRue et al., 2019; Milani et al., 2021) and by applying bibliometric techniques and multivariate analyses to a representative collection of documents that represent the canonical scientific literature on learning agility (Grau-Garcia et al., 2024).

The outcomes of this study will yield the following contributions: From both theoretical and practical perspectives, a more comprehensive and integrative model of the intellectual structure of learning agility. This will provide scientists, academics, and educators with the insights necessary to advance toward its unified conceptualization and development. Consequently, human resources professionals and practitioners will be closer to having more objective and reliable tools when identifying potential talent and facilitating leadership development.

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[2] Document pending publication due to being under review.

Similarly, educators will enhance the efficiency of applying this concept within their teaching methodologies. Lastly, from a methodological standpoint, the findings of this study hold significant value as they provide a clear entry point into complex areas of research by comparing different methodologies for determining an intellectual structure using the same dataset of documents.

2. Methodology

The research aims to identify and characterize the main themes within the construct of learning agility. Topic modeling was performed on the titles and abstracts of the 112 most influential documents identified in the prior work, "The intellectual structure of learning agility: A bibliometric study" (Grau-Garcia et al., 2024). After identifying various topics and research lines, the intellectual structure of learning agility was mapped and compared to the results of Grau-Garcia et al. (2024).

2.1. Methodology justification

This study employs clustering and a modified BERT approach for effective topic modeling. Topic modeling, an unsupervised machine learning technique widely used in Natural Language Processing ("NLP"), extracts specific themes or topics from extensive collections of unstructured texts such as articles and abstracts. These techniques group texts with similar meanings within a corpus.

Popular methods for topic modeling include Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), and Non-Negative Matrix Factorization (NMF). Recently, methods utilizing BERT for topic modeling (Devlin et al., 2019) have shown superior performance compared to NMF and LDA (Abuzayed & Al-Khalifa, 2021).

The BERT algorithm, introduced by Google in 2018, represents a significant advancement in Natural Language Processing ("NLP"). This neural network model is pre-trained on extensive text data using two main unsupervised tasks: Masked Language Modeling (MLM), where it predicts randomly masked words within sentences, and Next Sentence Prediction (NSP), which determines logical sequence continuity between two sentences in the original text. These tasks enhance its effectiveness across various "NLP" applications. BERT's training incorporates the SNLI (Bowman et al., 2015) and Multi-Genre NLI (Williams et al., 2018) datasets.

Unlike unidirectionally pre-trained models like ELMo (Peters et al., 2018a) and OpenAI GPT (Radford et al., 2018), which restrict architectures during pre-training, BERT is pre-trained bidirectionally. This capability allows BERT to capture deeper language context and word relationships from both directions within sentences, improving its understanding of word meanings. Consequently, BERT mitigates the constraints of unidirectional models, making it particularly advantageous for fine-tuning approaches by adding minimal task-specific parameters and fine-tuning the pre-trained parameters (Devlin et al., 2019).

BERT, based on a Transformer architecture, facilitates parallel data processing, enhancing efficiency and speed in handling large datasets. Through self-attention mechanisms, the model evaluates all words in a sentence, prioritizing their significance regardless of their position. This method generates deep contextual embeddings that account for word context, thereby improving the accuracy of semantic similarity assessments (Vaswani et al., 2017).

BERT, a pre-trained transformer network (Devlin et al., 2019), achieved remarkable performance in eleven "NLP" tasks, including question answering, sentence classification, and sentence-pair regression. It surpassed previous benchmarks across various evaluation metrics such as GLUE score, MultiNLI, and SQuAD Test F1 (Devlin et al., 2019).

In our study focusing on "NLP" tasks, particularly sentence-pair regression tasks like semantic textual similarity (STS), a Siamese structure is employed. This structure processes two input sentences through the transformer network to identify the most similar sentence pair and generate vector representations (i.e., embeddings) for entire sentences, capturing semantic meaning beyond individual words. Ultimately, BERT transforms text inputs (i.e., abstracts) into high-dimensional embeddings, where each unit of text is weighted based on its contextual relevance within the input.

However, due to the significant computational overhead, the original design of BERT is impractical for semantic similarity search and unsupervised tasks like clustering. Therefore, this study utilizes a modified version of the pre-trained BERT network that integrates a dimensionality reduction technique based on UMAP (Uniform Manifold Approximation and Projection) (McInnes et al., 2020). UMAP is renowned for reducing embedding dimensionality while preserving the global structure, producing semantically meaningful sentence embeddings (i.e., fixed-size vectors) suitable for topic modeling.

These embeddings are compared using cosine similarity, enabling efficient prediction of target values and grouping of semantically similar texts closely together. This approach significantly reduces the time required for identifying similar pairs from 65 hours with BERT/RoBERTa to approximately 5 seconds, maintaining the accuracy achieved by BERT and surpassing other state-of-the-art sentence embedding methods (Reimers & Gurevych, 2019). The output is then passed through an essential regression function to determine the final label, thereby adapting BERT for tasks previously deemed unsuitable, including large-scale semantic similarity search and clustering (Reimers & Gurevych, 2019).

In contrast to standard BERT, the modified version of the BERT network used in our study is pre-trained using masked language modeling and permuted language modeling techniques, enhancing both pre-training efficiency and performance. This innovative architecture addresses the limitations of the original BERT model by capturing nuanced contextual information and dependencies between words, yielding superior results across various natural language processing tasks.

After generating embeddings, texts with similar meanings are clustered together, revealing the underlying thematic structure of the texts. Clustering, a robust unsupervised machine learning algorithm, is widely employed to extract information from unstructured textual data and facilitate topic modeling. Given that the computational complexity of clustering algorithms increases with the number of features, dimensionally reduced embeddings are recommended to enhance performance. Experimental results demonstrate that clustering with dimensionality reduction facilitates the inference of more coherent topics (George & Sumathy, 2023).

In summary, topic modeling is a robust tool for comprehending and organizing large textual datasets by automatically identifying primary themes or topics within the data—specifically abstracts in our study—and clustering them accordingly. This methodology helps organize, understand, and summarize vast amounts of textual information, uncovering latent topics that vary across documents within a given corpus.

Additionally, BERT's ability to comprehend language context and semantics has made it a seminal model in “NLP,” driving significant advancements in diverse applications and setting new standards for language understanding models.

As data volumes exponentially increase and human processing capacities remain finite, the prompt and accurate understanding of topics from available data becomes crucial. Therefore, a clustering and BERT-based approach to topic modeling has become increasingly prevalent for analyzing unstructured textual data and automatically uncovering abstract topics within it. Consequently, numerous researchers have adopted these techniques to achieve similar objectives, aligning with the requirements of this study.

Finally, following an extensive literature review, it is apparent that this methodology addresses a specific and previously unmet need in the field.

2.2. Dataset

To identify the most influential works on learning agility, Grau-Garcia et al. (2024) initially retrieved 36 works from the Web of Science Core Collection using "learning agility" as a title keyword. Next, 2,216 bibliographic references were extracted. After removing duplicates, 1,625 unique cited documents remained.

Citation analysis, based on the assumption that frequently cited documents have a more significant impact, was conducted to identify the most influential works. Works cited three times, or more were included, resulting in 65 cited works. Additionally, 47 documents were included based on citations in five key papers and the authors' expertise, ensuring a diverse range of sources and critical concepts (Grau-Garcia et al., 2024).

A total of 112 titles and abstracts from the most influential works on learning agility, identified by Grau-Garcia et al. (2024), were reviewed (See Appendix 1 for the list of the most influential works according to Grau-Garcia et al. (2024)). Missing abstracts were replaced with executive summaries or book introductions.

For two documents without these, only titles were considered (Kolb, 1984; Burke et al., 2016). This analysis covered research from 1936 to 2022 and included only English texts. Titles and abstracts were preferred over full manuscripts for public accessibility and conciseness. Finally, a text in the form of a quotation, “Learning Agility Equals Leadership Success” (Ryan, 2009), was removed. As a result, the final list for thematic analysis comprised 111 texts.

2.3. Topic modeling

A Natural Language Processing (NLP) technique known as topic modeling was utilized to identify themes from the 111 abstracts of the most influential works on learning agility. Our study employed abstract clustering with HDBSCAN using the embeddings generated by a modified version of the BERT network and dimensionally reduced with UMAP. Additionally, class-based TF-IDF (c-TF-IDF) was employed to identify the most relevant words in each cluster and visualize the clustering results.

Various Python libraries and techniques were employed for these tasks: generating embeddings, reducing dimensionality, applying clustering algorithms, and visualizing the results. The methodology is outlined step-by-step below (See Appendix 2 for details and corresponding Python code).

Step 1. Importing the required libraries.

Step 2. Loading the pre-trained model.

Step 3. Defining the list of texts for processing.

Step 4. Generating embeddings for the abstracts.

Step 5. Application of UMAP for dimensionality reduction.

Step 6. Application of HDBSCAN for abstract clustering.

Step 7: Printing the clustering results for document.

Step 8. Identification of Key Topics using c-TF-IDF.

Step 9. Grouping the documents by cluster.

Step 10. Calculating c-TF-IDF for cluster.

Step 11. Displaying the most relevant words for cluster.

Step 12. Printing the clusters and the corresponding documents.

Step 13. Visualization of abstract clustering in reduced UMAP space using HDBSCAN.

3. Results

3.1. Description of topics

Once the input abstracts were processed through the modified BERT model, they were transformed into high-dimensional and deeply contextual embeddings. As previously mentioned, UMAP was utilized to reduce embedding dimensionality, generating semantically meaningful abstract embeddings or vectors.

These vectors were then compared using a cosine function. Given that the model was parameterized for a number of components equal to two and the distance measure for calculating similarity relationships between points was "cosine," the abstract embeddings were projected into a two-dimensional space. The proximity between points in this space represented the similarity of the abstracts.

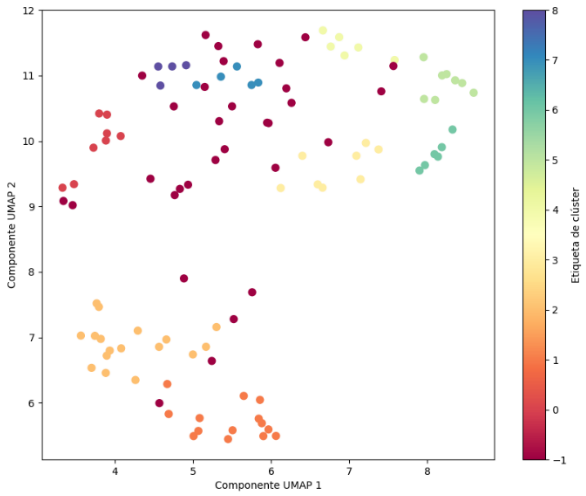
When clustering abstract embeddings using the HDBSCAN model, two clusters of maximum quality were identified using the following parameter values, corresponding to the most optimal Silhouette Score: {'min_cluster_size': 4, 'hdbscan_metric': 'euclidean,' 'extraction_method': 'eom'} (See Appendix 3 for details and corresponding Python code). However, by prioritizing the identification of a greater number of clusters over the quality of the clusters formed, we adjusted the parameters to: {'min_cluster_size': 4, 'hdbscan_metric': 'euclidean,' 'extraction_method': 'leaf'}.

This adjustment resulted in the identification of eight clusters, as the 'leaf' extraction method is more sensitive than 'eom' for the same remaining parameters. Figure 1 represents the abstract vectors in a two-dimensional map for this new combination of parameters.

Each point represents an abstract, and abstracts of the same color pertain to the same cluster, thereby centering around the same topic.

Figure 1.

Representation of the abstracts and the abstract clusters identified on a two-dimensional map for the following combination of parameters: {'min_cluster_size': 4, 'hdbscan_metric': 'euclidean,' 'extraction_method': 'eom'}



Source: The authors (2024).

Eight clusters or their corresponding topics were identified, each with a different number of abstracts assigned. Table 1 shows the number of abstracts by cluster or topic.

Table 1.

Number of abstracts per cluster

Cluster	Number of abstracts	%
-1	35	31,5
0	8	7,2
1	14	12,6
2	17	15,3
3	8	7,2
4	6	5,4
5	8	7,2
6	6	5,4
7	5	4,5
8	4	3,6
Total	**111**	**100%**

Source: The authors (2024).

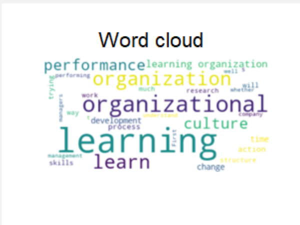
The cluster labeled "0" comprises eight abstracts, which represent 7.20% of the total abstracts (See Appendix 1 for a description of the abstracts in this cluster). The works in this cluster focus on "Experiential Learning Organizations," which differs from organizational adaptation, as an organization can adapt to changes without learning anything (Fiol & Lyles, 1985). In turn, Garvin et al. (2008) provide us with a tool that helps us build a learning organization in three steps, allowing us to assess progress at three different levels (i.e., individual, team, and company) (Garvin et al., 2008).

The learning culture and leadership are undoubtedly essential factors in building learning organizations (Hill, 1996). In constructing the learning organization, organizations face the dilemma of learning (i.e., exploration) versus performing (i.e., exploitation) (March ,1991). Given this dilemma and the rapid pace of change that causes organizations always to lag, organizations must consider the shift from “getting more performance into the learning process” to “getting more learning into the performance process” and sometimes “learn as you go”. (Baird et al., 1999). However, organizations sometimes hinder experiential learning or on-the-job learning. Finally, the relationship between organizational learning culture and other variables is assessed (Snell, 1992). Refer to Appendix 1 for the list of the most influential works on learning agility according to Grau-Garcia et al. (2024) in cluster “0”.

The most significant words in the cluster, as visualized in the word cloud, are presented in Figure 2, titled “The most significant words based on TF-IDF in Cluster 0”, where common or generic words (e.g., “of,” “the,” “and,” “with”) that frequently appear in most texts have been removed. This corroborates the definition of the topic for cluster 0. Words like “learning”, “experiential”, “experience”, “organizational”, “organization”, “organizations”, and “culture” align with the identified topic title.

Figure 2.

The most significant words based on TF-IDF in cluster “0”



Word	TF-IDF Score
learning	1.467
experiential	0.875
experience	0.873
source	0.873
organizational	0.604
organization	0.356
organizations	0.263
culture	0.227

Source: The authors (2024).

The cluster labeled “1” comprises fourteen abstracts, representing 12.60% of the total abstracts (See Appendix 1 for descriptions of the abstracts in this cluster). One additional topic is identified. In this case, most of the works focus on the key traits, characteristics, and behaviors that differentiate upper-level management positions and top executives from those who have derailed, aiming to develop the next generation of effective leaders (Lombardo et al., 1988; McCall, 1998; McCall & Lombardo, 1983; Bray et al., 1974). Hogan et al. (2009) highlight the importance of this issue and underscore, through an empirical study, that nearly half of leaders fail, on average (Hogan et al., 2009).

Additionally, considering that the qualities of effective leadership and the interaction between leadership styles within a group depend on the situation (Fiedler, 1967), the amount of freedom available to subordinates in reaching decisions (Tannenbaum & Schmidt, 1973), and their decision-making processes (Brousseau et al., 2006;Vroom & Yetton, 1973), the style of effective leadership must be flexible to handle shifting priorities, problems, and situations (Norton, 2010).

In this context, Kaiser and Craig (2011) focus on the development of flexible and adaptive leaders across different levels of the organizational hierarchy, which resemble the various situations that leaders need to face.

Flexible leadership is defined as meta-competence and integrates some of the most critical components of learning agility (e.g., a comprehensive behavioral repertoire, a learning orientation to develop it, and an ability to remain open to learning in novel situations). Previously, Freedman (1988) had identified five career pathways and crossroads where leaders are confronted by more challenges and, consequently, changes in the situation.

Therefore, this topic is defined as "Adaptive and Flexible Leadership: Navigating Situational Challenges at Each Level of the Organizational Ladder for Executive Success and Career Effectiveness." See Appendix 1 for the list of the most influential works on learning agility in cluster "1".

Figure 3, titled "The most significant words based on TF-IDF for Cluster 1", displays the most significant words in the cluster, as shown in the word cloud. This supports the definition of the topic for cluster 1. Words like "executive", "effectiveness", "successful", and "derailed" align with the identified topic title.

Figure 3.

The most significant words based on TF-IDF in cluster "1"

Word	TF-IDF Score
leadership	0.650
managers	0.537
executives	0.482
effectiveness	0.479
successful	0.419
managerial	0.374
derailed	0.364
leaders	0.348
decision	0.328
executive	0.310

Source: The authors (2024).

Regarding the cluster labeled "2", it comprises seventeen abstracts, representing 15.30% of the total abstracts. The works in this cluster focus on identifying potential talent (Church, 2015), many of which are based on the ability to learn from experiences (Spreitzer,1997) and on the continuous development of leadership (Church et al., 2015; McCauley, 2002) across organizational levels (Amagoh, 2009; Day & Harrison, 2007).

Colquitt and Simmering (1998) apply these concepts in the construction of leadership succession plans. This is based on the belief that leaders are not only born but can also be made (Bennis, 1989), with experiences identified as the primary source of learning (DeRue & Wellman, 2009). If leadership is learned to a certain extent, it is learned through experiences (McCall, 2010) with specific characteristics (DeRue & Wellman, 2009). In this context, the involvement of senior management in development programs (e.g., mentoring) is considered a best practice (DeRue & Ashford, 2010). Similarly, Ohlott (2004) emphasizes the importance of job assignments in leadership development.

Thus, the potential is defined as the ability to take advantage of developmental experiences that will be offered (McCall, 1994) or, in other words, being developmentally ready to engage in leader development (Avolio & Hannah, 2008). Therefore, experience itself is necessary but not sufficient (Dominick et al., 2010). Hence, a prerequisite for any leadership development program is the possession or development of the capacity (Avolio & Hannah, 2008) to fully leverage experiences to accelerate development and gain maximum benefit through internalization (i.e., learning to lead) (Van Velsor, 2013).

Consequently, potential competency models for improving current performance are meaningless unless they are based on learning and suggest potentially helpful experiences or training for executives or lower-level managers who aspire to become executives (Briscoe & Hall, 1999; Dai & De Meuse, 2011). As a result, this topic is titled "Talent Potential Identification and Leadership Development Based on Learning Experiences." See Appendix 1 for the list of the most influential works on learning agility in cluster "2".

Figure 4, under the title "The most significant words based on TF-IDF for Cluster 2", presents the most significant words in the cluster, as depicted in the word cloud. Words like "leadership", "development", "developmental", "leaders", "potential", "experiences", "experience", and "assignments" align with the identified topic title.

Figure 4.

The most significant words based on TF-IDF in cluster "2"

Word	TF-IDF Score
leadership	1.333
development	1.140
developmental	0.524
leaders	0.511
experience	0.510
leader	0.454
potential	0.451
job	0.441
executive	0.431
framework	0.347
assignments	0.340
experiences	0.334

Source: The authors (2024).

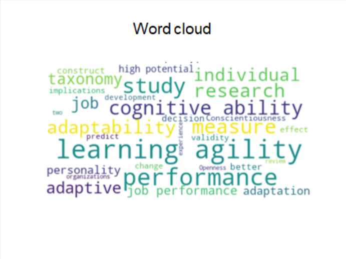
The cluster labeled "3" comprises eight abstracts, which represents 7.20% of the total abstracts (See Appendix 1 for descriptions of the abstracts in this cluster). Learning agility can predict the job performance of a task above and beyond cognitive ability and personality (Connolly, 2001). In contrast, job performance does not predict high potential identification as effectively as learning agility does (Dries et al., 2012). In a changing context where any task performance takes place, performance adaptation at both individual and organizational levels is essential to continue succeeding (Baard et al., 2015; Ployhart & Bliese, 2006). Several studies explore the taxonomy of performance adaptation or adaptive performance (Baard et al., 2015; Pulakos et al., 2000).

As a result of Pulakos et al. 's study in 2000, the Job Adaptability Inventory was developed, a measure of individual differences in adaptability, which integrates eight dimensions (Pulakos et al., 2002; Pulakos et al., 2000). "If a measure of learning agility indicates anything, it should identify those who are more adaptable and more willing to confront tasks they do not yet know how to perform" (Eichinger & Lombardo, 2004). Consequently, we have named this cluster "Performance Adaptation and Relationships between Job Performance, High Potential, and Learning Agility."

See Appendix 1 for the list of the most influential works on learning agility in cluster "3". Figure 5, titled "The most significant words based on TF-IDF for Cluster 3", displays the most significant words in the cluster, as shown in the word cloud. Words like "adaptability", "performance", "adaptive", "adaptation", and "job" align with the identified topic title.

Figure 5.

The most significant words based on TF-IDF in cluster "3"



Word	TF-IDF Score
learning	0.495
adaptability	0.475
agility	0.460
performance	0.459
adaptive	0.430
cognitive	0.365
job	0.334
ability	0.326
taxonomy	0.325
individual	0.283
adaptation	0.249
personality	0.219

Source: The authors (2024).

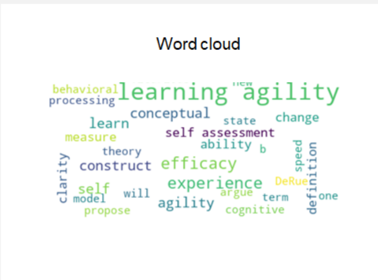
The cluster labeled "4" comprises six abstracts, representing 5.40% of the total abstracts. The works in this cluster are primarily, though not exclusively, centered on the quest for conceptual clarity, particularly regarding the concept of learning agility (Bandura, 1977). Following the validation of the first self-assessment tool for learning agility (De Meuse et al., 2011), based on an initial broader conceptualization of the construct by Lombardo and Eichinger (2000), a new, more focused philosophy emerged, emphasizing the speed and flexibility of experiential learning (DeRue et al., 2012).

Various studies highlight this new trend and its benefits and challenges (Arun, 2012; Mitchinson, 2012), culminating in 2016 with the introduction of a new model and its measure (Burke, 2016). Nonetheless, both philosophies coexisted from then on. Therefore, this cluster is labeled "In Search of Conceptual Clarity: Focusing on Speed and Flexibility in Learning Agility." See Appendix 1 for the list of the most influential works on learning agility in cluster "4".

Figure 6, which describes the Top TF-IDF Words in Cluster 4, exhibits the most crucial words found within the cluster, as depicted in the word cloud. Words like "clarity", "conceptual", "new" and "model" align with the identified topic title.

Figure 6.

The most significant words based on TF-IDF in cluster "4"



Word	TF-IDF Score
agility	1.298
learning:	1.208
measure	1.112
new	1.093
model	1.072
conceptual	0.280
assessment	0.271
efficacy	0.234
clarity	0.208
experience	0.206
ability	0.190
propose	0.168

Source: The authors (2024).

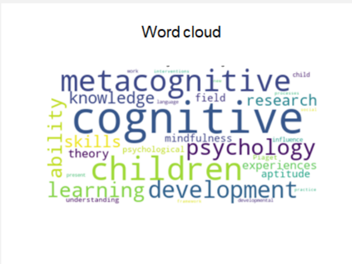
Cluster number "5" comprises eight abstracts, representing 7.20% of the total abstracts. Human behavior and perception are influenced by both external factors, such as social environments, cultural norms, and situational contexts, and internal factors, including individual personality traits, intelligence, and motivations (e.g., goal orientation) (Levin, 1936). Focusing specifically on the latter aspect (i.e., individual differences), several studies examine intelligence, metacognition, metacognitive knowledge, and their development (Piaget, 1936; Swanson, 1990), cognitive flexibility and its development (Deak, 2013), mindfulness (Shapiro, 2009), motivational patterns (Dweck, 1986), and aptitude (Swanson, 1990).

Lastly, Flavell (1979) underscores the need for cognitive knowledge and monitoring, which are essential for development. These works establish the foundational basis for future research on enhancing learning agility. Therefore, we designate the topic of this cluster as "Foundations of Individual Differences and Cognitive Development in Human Behavior: Implications for Learning Agility".

Figure 7, which presents the Top TF-IDF Words in Cluster 5, exhibits the most crucial words found within the cluster, as depicted in the word cloud. Words like "learning", "cognitive", "metacognitive", "development", "knowledge" and "motivational" align with the identified topic title.

Figure 7.

The most significant words based on TF-IDF in cluster "5"



Word	TF-IDF Score
cognitive	0.664
language	0.433
metacognitive	0.387
motivational	0.341
ability	0.322
children	0.321
learning	0.319
processes	0.309
development	0.301
knowledge	0.272
flexibility	0.267
psychology	0.259
aptitude	0.239
skills	0.238
mindfulness	0.231

Source: The authors (2024).

Cluster "6" comprises six abstracts, representing 5.40% of the total abstracts. With only six abstracts to define the topic within this cluster, the abstracts focus on various factors other than learning agility that directly impact performance, occupational attainment, and life success. These factors include practical and creative intelligence (Sternberg, 1997), general mental ability (GMA) introduced by Spearman in 1904, job knowledge (Hunter, 1986; Schmidt et al., 1986), job experience and deliberate practice (Ericsson, 2006; Schmidt et al., 1986). These studies are highly recommended as primary sources for the development of the learning agility process based on the latest conceptualization of the construct (DeRue et al., 2012), involving understanding, practicing, and likely gaining speed and flexibility over time.

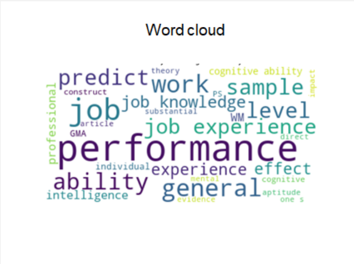
Continuing in this vein of enhancing learning agility, the study "Individual differences in working memory within a nomological network of cognitive and perceptual speed abilities (Ackerman, 2002) investigates the relationship of working memory with cognitive and perceptual speed. These components, along with cognitive flexibility, comprise the construct of learning agility as per the latest conceptualization (DeRue et al., 2012).

Thus, this cluster is titled "Other Factors Influencing Performance and Foundations for Learning Agility Development." This title effectively conveys that the cluster explores factors beyond learning agility that impact performance while also emphasizing the foundational aspects related to developing learning agility. It succinctly captures the essence of the cluster's focus. See Appendix 1 for the list of the most influential works on learning agility in cluster "6".

Figure 8 displays the primary words identified by TF-IDF in Cluster 6, showcased in the word cloud. Keywords such as "performance", "intelligence", "cognitive", "ability", "predicts", and "knowledge" correspond closely to the identified topic title.

Figure 8.

The most significant words based on TF-IDF in cluster "6"



Word	TF-IDF Score
job	0.757
performance	0.528
intelligence	0.492
cognitive	0.479
ability	0.404
experience	0.315
predicts	0.284
knowledge	0.281
sample	0.253
general	0.241
article	0.240
work	0.220
theory	0.213

Source: The authors (2024).

The cluster labeled "7" comprises five abstracts, representing 4.50% of the total abstracts. In this rapidly changing environment, organizations need to identify and develop leaders who can effectively manage change. From this need, the concept of learning agility emerged. Initially, it was a broad philosophy integrating motivation, the ability to learn from experiences, and the application of learned lessons to successfully handle new situations.

This concept was first coined by Lombardo and Eichinger in 2000 (Lombardo & Eichinger, 2000). Thus, this represents one of the foundational works in this discipline, initiating the first philosophy or stream in the conceptualization of learning agility.

Following this, perhaps the second most important work related to learning agility marks the beginning of a more focused stream, concentrating solely on the speed and flexibility of learning (DeRue, 2012). In the same year, De Meuse et al. (2012) quickly defended this conceptualization against criticism from DeRue et al. (2012).

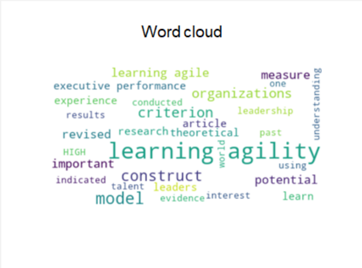
Finally, perhaps one of the most important contemporary works, "The Age of Agility: Building Learning Agile Leaders and Organizations," "brings together more than 50 authors with backgrounds in both academic research and talent management practice to address one of the most important trends in the business world over the past decade" (Harvey & De Meuse, 2021).

Lastly, unlike Smith's work in 2015, which we do not find relevant to this cluster, the remaining abstracts constitute four of the most significant studies to date concerning this research topic. Therefore, we have designated this cluster as "Origins and Learning Agility Foundations." See Appendix 1 for the list of the most influential works on learning agility in cluster "7".

Figure 9 showcases the most significant words identified through TF-IDF for Cluster 7, visually represented in the accompanying word cloud. While not perfectly aligned, these words could be indicative of the assigned topic title for the cluster.

Figure 9.

The most significant words based on TF-IDF in cluster "7"



Word	TF-IDF Score
agility	0.516
learning	0.510
model	0.202
learn	0.195
organizations	0.175
construct	0.146
potential	0.143
criterion	0.141

Source: The authors (2024).

The cluster labeled "8" comprises four abstracts, which represent 3.60% of the total abstracts. With only four abstracts to identify the topic, all the works appear to focus on the relationships between the organization (e.g., learning culture), agility (e.g., learning agility, agility-resilience), and various talent constructs: engagement (Saputra et al., 2018) and learning goal orientation (Yadav & Dixit, 2017), as well as organizational management constructs: operational excellence (Carvalho et al., 2019) and corporate financial performance (Pulakos et al., 2019).

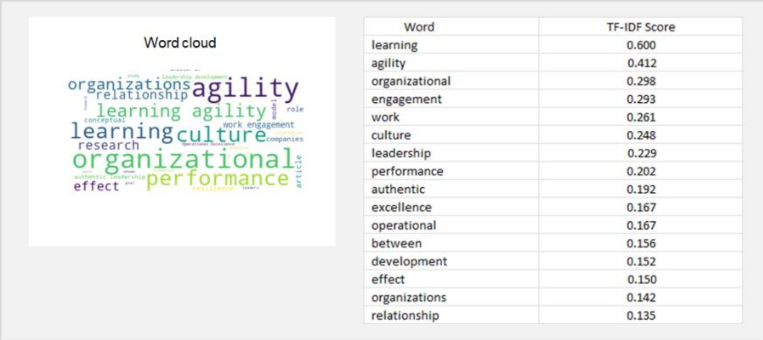
Notably, the mediating role of learning agility on the relationship between work engagement and learning culture (Saputra et al., 2018) is highlighted for its significance. Therefore, all the studies in this cluster are empirical. Additionally, in the topic labeled "-1," the study "Role of learning agility and learning culture on turnover intention: an empirical study" (Tripathi et al., 2020) might be more appropriately included in this cluster.

Therefore, we designate this cluster as "Interrelations of Learning Culture, Learning Agility, and Other Talent and Management Constructs: Mediating Effects of Learning Agility on learning culture". See Appendix 1 for the list of the most influential works on learning agility in cluster "8".

Figure 10 displays the primary words identified by TF-IDF in Cluster 8, visualized in the word cloud. Keywords such as "learning", "engagement", "culture", "between", "relationship", and "effect" correspond closely to the identified topic title.

Figure 10.

The most significant words based on TF-IDF in cluster "8"



Word	TF-IDF Score
learning	0.600
agility	0.412
organizational	0.298
engagement	0.293
work	0.261
culture	0.248
leadership	0.229
performance	0.202
authentic	0.192
excellence	0.167
operational	0.167
between	0.156
development	0.152
effect	0.150
organizations	0.142
relationship	0.135

Source: The authors (2024).

The cluster labeled "-1**"** represents the set of abstracts that were too sparse to categorize. Interestingly, this cluster is also the most extensive set of abstracts, comprising thirty-five abstracts, which accounts for 31.50% of the total abstracts. These abstracts do not fit well into the patterns of the main clusters previously identified. Many causes explain this. Abstracts that are excessively brief or vague, thematically diverse or unique, and anomalous or outliers are among those that complicate classification.

Based on the author's familiarity with the study object, abstracts in cluster "-1" may fit within the nine clusters previously identified or generate new ones not identified thus far. Some examples of the former case are as follows: "Learning agility: A construct whose time has come" (De Meuse et al., 2010) assigned to cluster 7; "Learning agility: Its evolution as a psychological construct and its empirical relationship to leader success" (De Meuse, 2017), "A meta-analysis of the relationship between learning agility and leader success" (De Meuse, 2019), and "Prioritizing the learning agility research agenda" (Hezlett & Kuncel, 2012) assigned to cluster 4; "Lessons of experience: How successful executives develop on the job" (McCall et al., 1988) assigned to cluster 2; "The role of learning agility in executive career success: The results of two field studies" (Dai et al., 2013) assigned to cluster 3; or perhaps "Examining characteristics of high potential" (Juhdi, 2012) assigned to cluster 1. These are just some examples.

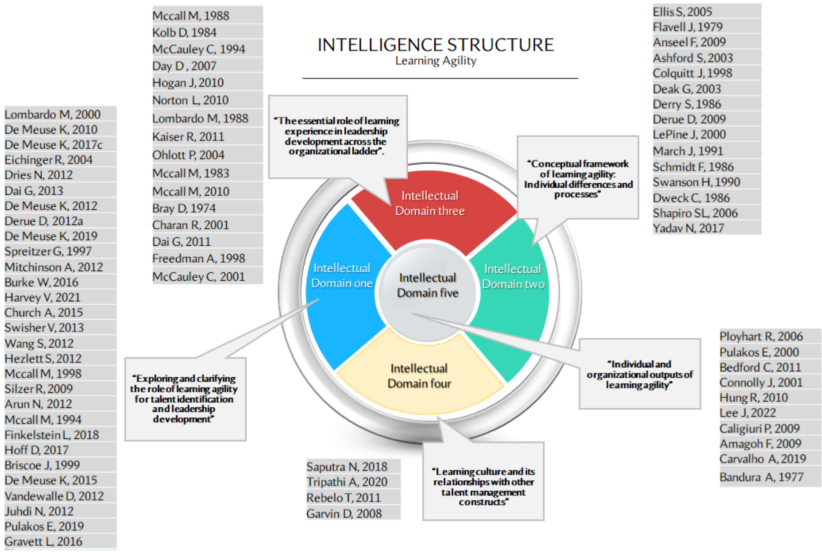
On the other hand, other works such as "After-event reviews: drawing lessons from successful and failed experiences" (Ellis & Davidi, 2005), "Coaching for learning agility: The importance of leader behavior, learning goal orientation, and psychological safety" (Drinka, 2018), "Reflection as a strategy to enhance task performance after feedback" (Anseel et al., 2009), "Reflections on the looking glass: A review of research on feedback-seeking behavior in organizations" (Ashford et al., 2003), "Feedback-seeking behavior of new hires and job changers" (Brett, 1990), and finally "Newcomer information seeking: Exploring types, modes, sources, and outcomes" (Morrison, 1993) are examples of documents that might constitute a new cluster or a sub-cluster within cluster "2", "Talent Potential Identification and Leadership Development Based on Learning Experiences," aimed at fully leveraging experiences and gaining maximum benefit through internalization. Thus, this sub-cluster within cluster "2.1" or the new cluster, labeled as "9", is termed "Behavioral processes to maximize or leverage learning from experiences". See Appendix 1 for the list of the most influential works on learning agility in cluster "-1".

3.2. Comparative analysis of methodologies

According to Grau-Garcia et al. (2024), five distinct fields of knowledge or intellectual domains were identified using co-citation techniques. These domains constitute the intellectual structure of learning agility. These fields of knowledge or intellectual patterns are described in the following figure:

Figure 11.

The intellectual structure of learning agility using co-citation techniques



Source: Grau-García et al. (2024).

Based on the author's familiarity with the research topic, we can establish a relationship between both clusterings, topics, or intellectual domains, five identified with co-citation techniques and nine through a modified BERT model for topic modeling, as shown in the following table.

Table 2.

Relationship between clusters identified using both techniques for the same set of documents

Cluster number	Clusters identified using a modified BERT model for topic modeling	Clusters identified using co-citation techniques
0	“Experiential Learning Organizations”	“Learning culture and its relationships with other talent management constructs”
1	“Adaptive and Flexible Leadership: Navigating Situational Challenges at Each Level of the Organizational Ladder for Executive Success and Career Effectiveness.”	“The essential role of learning experience in leadership development across the organizational ladder.”
2	“Talent Potential Identification and Leadership Development Based on Learning Experiences”	“The essential role of learning experience in leadership development across the organizational ladder.”
2.1	“Behavioral processes to maximize or leverage learning from experiences”	“Conceptual framework of learning agility: Individual differences and processes"
3	“Performance Adaptation and Relationships between Job Performance, High Potential and Learning Agility “	“Individual and organizational outputs of learning agility,” “Exploring and clarifying the role of learning agility for talent identification and leadership development,”
4	“In Search of Conceptual Clarity: Focusing on Speed and Flexibility in Learning Agility “	“Exploring and clarifying the role of learning agility for talent identification and leadership development.”
5	“Foundations of Individual Differences and Cognitive Development in Human Behavior: Implications for Learning Agility “	Conceptual framework of learning agility: Individual differences and processes."
6	“Other Factors Influencing Performance and Foundations for Learning Agility Development “	Conceptual framework of learning agility: Individual differences and processes."
7	“Origins and Learning Agility Foundations “	“Exploring and clarifying the role of learning agility for talent identification and leadership development.”
8	“Interrelations of Learning Culture, Learning Agility, and Other Talent and Management Constructs: Mediating Effects of Learning Agility on Learning culture “	“Learning culture and its relationships with other talent management constructs”

Source: The authors (2024).

Consequently, scientists can quickly and easily access the most relevant documents to date in a specific research area or topic within the construct of learning agility and have a complete perspective of the different fields investigated thus far (See Appendix 1 for a detailed description of the abstracts in each cluster).

Moving forward, an integrated conceptualization of learning agility that synthesizes the various philosophies of learning agility that have emerged thus far is essential. This includes understanding its development in leadership, which is pivotal for developing other leadership competencies. Documents from sub-cluster 2.1 and clusters 4, 5, and 6 identified in this study, as well as those from the “Conceptual framework of learning agility: Individual differences and processes” cluster in Grau-Garcia et al. (2024), are instrumental in achieving this goal.

4. Conclusions

Applying a modified BERT model for topic modeling, 111 titles and abstracts on learning agility were analyzed to identify the predominant research topics within this field. These findings revealed eight distinct thematic lines. Additionally, leveraging their familiarity with learning agility, the authors identified an additional topic within cluster "-1": "Behavioral processes to maximize or leverage learning from experiences". In total, nine research lines were delineated in this study: eight through topic modeling and one additional line based on the authors' expertise in learning agility and talent management practices.

Comparing these results with those of Grau-García et al. (2024) (See Figure 11), who identified five research lines through co-citation techniques, reveals that each of the nine clusters or topics identified in this study encompasses one or more topics identified through co-citation analysis. This suggests that topic modeling can offer finer granularity in identifying topics in this case, thereby providing deeper insights into the intellectual structure of the construct.

Furthermore, given that more than 30% of the abstracts were assigned to cluster "-1", a meticulous individual review is essential. Drawing on the author's insights and leveraging co-citation techniques are crucial for accurately assigning these abstracts to a previously identified cluster or helping identify new topics within the cluster "-1".

Consequently, we conclude that utilizing citation techniques to identify the most influential works in any research discipline or construct, combined with co-citation techniques and thematic classification algorithms based on BERT architecture, enhances the efficiency and accuracy of text classification. This highlights the potential advantages of natural language processing technologies in scientific research. Therefore, these combined technologies add significant value in characterizing and identifying important research trends from extensive collections of scientific publications.

Additionally, these complementary findings are precious, offering researchers, practitioners, professionals, and educators a comprehensible introduction to this intricate research area. They deepen understanding and provide a broader perspective, laying the most relevant groundwork thus far for exploring new theoretical questions, which may lead to the development of new theories grounded in existing ones (Ritzer, 2001). Consequently, the foundation to refine the conceptualization of learning agility and its measurement is established, thereby advancing the field.

In the long term, this enhanced understanding may provide HR professionals and practitioners with the necessary tools to make more informed decisions in talent management, leadership development, and high-potential identification. Ultimately, it may enable individuals and organizations to navigate challenges and seize opportunities in today's dynamic environment. Reaching a consensus on this construct, as well as its definitive discriminant and predictive validation, may also benefit other HR domains and scientific fields, including educational methodologies and technologies.

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