A Comparative Analysis of Embedding Models and Traditional Methods for Publication Selection in Systematic Literature Reviews - A Case Study in Gamification Marketing

Paweł Karol Frankowski
Maritime University of Szczecin, Faculty of Computer Science and Telecommunication
Szczecin, Poland *p.frankowski@pm.szczecin.pl*

Joanna Wiśniewska
University of Szczecin, Institute of Management
Szczecin, Poland *joanna.wisniewska@usz.edu.pl*

Sebastian Matysik
University of Szczecin, Institute of Management, Doctoral School
Szczecin, Poland *sebastian.matysik@usz.edu.pl*

Abstract

This study aimed to compare the effectiveness of the deep ANN embedding technique with traditional article selection methods in systematic literature reviews. The embedding model utilizes a natural language problem description to find semantically similar publications. Consequently, this technique is accessible to users without experience in data exploration. Traditional methods are represented by precise keyword queries in Scopus and Excel-based selection. Keywords used in these methods are extracted from the description by the GPT-4o model with a temperature set to zero, ensuring repeatability. The obtained results were evaluated using bibliometric metrics, which facilitate the assessment of similarities among filtered publications and enhance understanding of their connections. The findings demonstrated the superiority of the embedding model, achieving higher thematic coherence and more shared references and keywords. This approach improves the identification of relevant publications and significantly contributes to automating systematic literature reviews, which is desired in many scientific disciplines.

Keywords: embedding models, systematic literature review, bibliometric analysis, semantic similarity, publication selection.

1. Introduction

1.1 Motivation

Systematic literature reviews (SLR) play a crucial role in the early stages of research by offering a structured and objective synthesis of existing knowledge. They often serve precisely to establish the current state of knowledge and research [9]. This methodology minimizes the risk of errors and bias through a transparent and replicable source selection process [19]. In contrast to narrative literature reviews, systematic reviews provide a comprehensive approach to the subject. They also support evidence-based decision-making. Transparency is achieved through clearly defined search strategies and inclusion or exclusion criteria [19], enhancing the credibility of the results and enabling the identification of research gaps [35].

The SLR process includes several key stages: planning (formulating research questions, defining the scope, and developing a protocol), comprehensive literature searching, applying pre-defined selection criteria, data extraction, and synthesis. All these steps must be documented to maintain methodological rigour [9], [24], [43]. It is also essential to report the findings in detail and with transparency. Systematic reviews help organize diverse theoretical perspectives and promote the development of coherent theoretical frameworks or create a new one [11].

Bibliometric analysis complements SLR by enabling quantitative examination of knowledge structures within a field through relationships among publications, authors, and theories [26], [38]. Tools like HistCite, CiteSpace, VOSviewer and bibliometrix also visualize citations and identify key research streams [3], [38]. In management sciences, where replication studies are scarce and definitions vary, bibliometric analysis helps develop solid theoretical foundations. This improves the understanding of research concepts and trends [11], [45].

The Scopus database produced 46305 publications for the query "systematic literature review," concentrating on the titles, abstracts, and keywords of articles published between 2018 and 2024. Fig. 1 illustrates a notable rise in scientific publications discussing SLR during the analyzed years, emphasizing the increasing adoption of the systematic literature review approach in management-related topics.

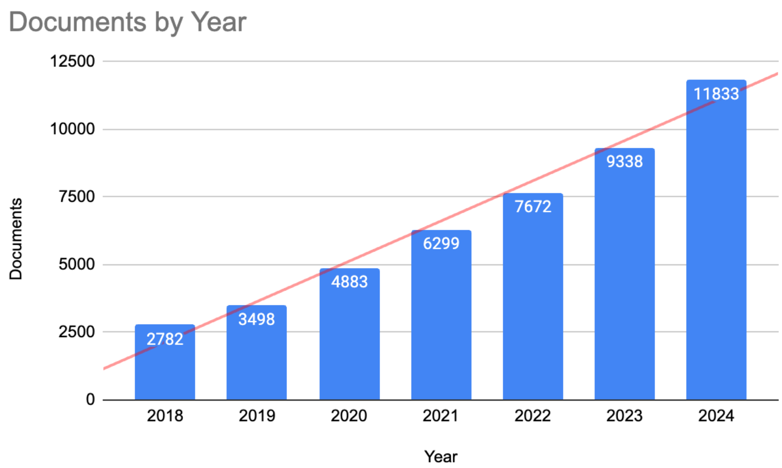


Fig. 1. Total number of publications on SLR published between 2018 and 2024 [Scopus]

Fig. 2 shows an analysis of the popularity index from Google Trends that identifies a significant increase in interest in the keyword ‘systematic literature review’ between 2018 and 2024.

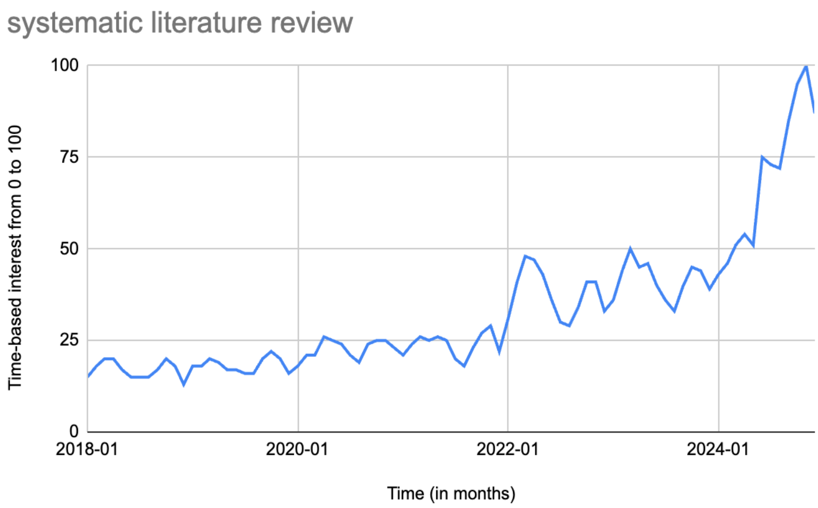


Fig. 2 The Google Trends Popularity Index for the keyword: systematic literature review from 2018 to 2024

Both charts indicate a growing interest in the systematic literature review method from 2018 to 2024. Scopus data show an apparent rise in scientific publications using this method, while Google Trends confirms increased search interest, particularly from 2022 onward. Together, they highlight intensified practical application and interest in SLR.

We are in the information age, where approximately 400 million terabytes of data are uploaded daily, totaling around 147 zettabytes (10^{21}B) annually by 2024. It is estimated that 90% of the world's data was created in the past two years [12]. A significant portion of this data is generated by artificial intelligence (AI), which has also transformed the preparation and utilization of scientific publications at every stage of manuscript development [36]. While AI cannot independently compose scientific articles [22], its influence on global science is rapidly increasing. The trend is evident: the proportion of AI-generated content is set to rise systematically in the coming years, which could lead to unforeseen and potentially harmful outcomes. One primary concern is that AI tends to average results, marginalizing less popular views, opinions, or research findings. Another major issue arises when AI systems are trained predominantly on data generated by other AI systems. This can lead to a so-called "model collapse". This phenomenon occurs when the system overwrites the rarer elements of its original training data. This results in inconsistent or meaningless results [44]. These emerging trends suggest that soon, the challenge will not be finding answers to questions but assessing the validity of those answers will be key. Consequently, with the rise of generative AI and the accompanying increase in information noise and nonsensical data, there is an urgent need to develop robust techniques for information filtration. A systematic literature review is the most popular and practical methodology for identifying the current state of knowledge. That is why it is so important to update it to the realities of the 21st century.

Using traditional keyword searches to find publications is inadequate in the age of AI-generated content, necessitating the development of more effective techniques. Theoretically, embedding methods should help SLR systems understand context and language nuances, enabling the retrieval of relevant results without exact keyword matches. This approach typically increases accuracy by accommodating synonyms and related concepts. The proposed method is user-friendly, even for those without data science expertise. Semantic search enhances the understanding of user intent and personalizes outcomes based on user preferences, tailoring searches to meet individual needs. Their resistance to manipulation ensures that meaning, rather than keyword frequency, guides the results. This study evaluates the effectiveness of the embedding method against two widely used traditional SLR keyword-based techniques [28].

This article is part of a series of publications on artificial intelligence-based automation in systematic literature reviews.

1.2. Systematic Literature Review

The publication selection process in SLR is vital for ensuring reliability and credibility. An initial step in this process involves formulating a straightforward research question and specific inclusion and exclusion criteria [29]. This typically includes selecting appropriate study designs and publication types to minimize biases such as publication and language bias [29]. Customized selection forms and predefined protocols guide this process, often involving at least two independent reviewers to enhance reliability [34]. Disagreements are resolved through discussion or mediation. This approach ensures transparency in reporting [1], [4], [31].

Selection starts with keyword searches in electronic databases, followed by screening titles and abstracts to assess relevance [20], [39]. Reviews often use classification systems to categorize publications before conducting full-text analysis [20]. For example, Santos et al. [37] excluded more than 270 sources after reviewing keywords and abstracts. Some reviews indicate which parts of publications informed decisions, enhancing transparency [20]. A structured, documented approach is vital for maintaining credibility [20], [39].

The selection process starts with searching of the keywords corresponding to the research question, which are assessed for thematic consistency [18], [20], [39]. The next step is screening of the titles of articles and abstracts to evaluate a content and its' suitability to examined problem. [7], [20]. The only publications that meet above mentioned criteria are proceed to full-text analysis to verify if should be include or reject [20], [39]. Then the classification systems organize studies by relevance to facilitate prioritization [20].

There are some additional considerations in the process of selection of literature to review for example: to include prioritizing some types of studies that suites to objectives of our review, such as randomized controlled trials or to include the most influential studies, which could be identified by citation counts [20]. There is also possibility to mitigate the publication bias by including „grey literatury" such as conference abstracts [7], [44]. Duplicate removal and language considerations are also vital. [29]. Some reviews consider citation counts to highlight influential studies or manage extensive literature [20].

Despite enhancing structure and reliability, these techniques some have limitations. For example, as consider the keyword searching you should notice possibilities of overlooking relevant studies only due to alternative terminologies used as keywords. The same applies to screening only by title or abstract could provide to exclude some valuable researching works, which are identifiable only upon full-text review. Therefore, it should be stated that classification systems introduce some kind of risks of potentially omitting essential studies if you do not relay on all important parameters for example the relying on citation counts may favor established work over emerging research, restrictions made on language or format of publications always lead to narrowing the scope of review.

The process of literature review providing in the above mentioned way requires significant efforts (sometimes needs multiple reviewer involvement) and is time-consuming.

2. Methodology

The research compared the new approach to traditional publication selection methods using various bibliometric indicators. We utilized our custom software, developed in Python and operated within the Google Colab environment. The architecture of the software consists of data ingestion, text preprocessing (title and abstract merging), embedding generation using the all-distilroberta-v1 model from the sentence-transformers library, cosine similarity calculation, and output ranking of articles based on semantic relevance. This process is executed in a modular pipeline within Google Colab, allowing for flexible embedding model selection and batch processing to handle large-scale bibliographic datasets efficiently. As preliminary studies were made on the comparison of different embedding models in the literature selection process, the all-distilrobert-v1 model, which was the most promising in terms of the results obtained, was selected. This developed specialised tool streamlines the entire analysis process and also calculates relevant bibliometric indicators. Two key bibliometric indicators were applied to assess the method's effectiveness: shared keywords and shared references. The shared keywords metric primarily evaluates subject matter similarity across publications, while shared references identify significant works and thematic clusters [23], [36].

The research began with formulating a research problem, framed for this article around how gamification mechanisms are used in marketing activities and their impact on consumer loyalty and engagement.

Research problem: How is gamification used in marketing activities? Does gamification affect consumer loyalty and engagement? What specific gamification mechanisms are most commonly used in marketing campaigns? The use of gamification mechanisms in marketing activities and their impact on consumer loyalty and engagement.

The data was sourced from the Scopus database, a popular choice for researchers conducting systematic literature reviews. We chose Scopus, which is more effective than Google Scholar for systematic literature reviews because of its higher citation value and precision, better metadata quality, and advanced filtering and retrieval capabilities. These features make it more suitable for identifying peer-reviewed literature [2]. Scopus was chosen as the data source for this study because it includes more than 40000 peer-reviewed scientific journals, making it the largest multidisciplinary database, surpassing Web of Science, which indexes around 24000 journals [6]. Additionally, Scopus offers an intuitive interface, advanced search capabilities, more data for bibliometric analysis, which is crucial for transparency and reproducibility of the research process [6]. Initially, a broad search using the query "gamification" AND "marketing" produced a preliminary collection of 14302 scientific publications. Following this, three distinct selection methods were implemented.

The first approach utilized the all-distilroberta-v1 embedding model by combining the title and abstract of each publication into their representation, then generating a vector representation with the model. A corresponding vector was also created for the research problem. This enabled the calculation of the cosine distance between the research problem vector and the vectors of each publication. The cosine distance acts as a gauge for textual similarity [40]. It ranges from 0 to 2, where a distance of 0 signifies identical vector directions (i.e., the exact text), while a distance of 2 denotes maximal difference (opposite directions), as represented by formula (1).

The similarity of the problem description to each identified publication is assessed using cosine distance, as shown in equation (1).

$$\text{distance}(u, v) = 1 - \frac{u \cdot v}{\|u\| \, \|v\|} \tag{1}$$

For further analysis, 17 documents with the lowest distance values (semantically closest to the research topic) were chosen based on the cosine distance calculated using formula (1).

The second method was based on a narrowed query constructed using keywords extracted from the primary research problem by the GPT-4o model. The extraction was conducted in the OpenAI Playground, with the temperature parameter set to 0 for maximum result repeatability. This parameter modulates the creativity of the language model. The process produced a selection of pertinent phrases, including “Gamification”, “Marketing”, “Consumer loyalty”, “Consumer engagement”, “Mechanisms”, “Marketing campaigns”, “Influence”, and “Impact”. A query was constructed using these terms, incorporating the OR operator for terms like “influence” and “impact,” as well as variations such as “consumer loyalty” and “consumer engagement.” The search was performed in Scopus, covering all publication fields, resulting in a focused selection of 15 articles that align closely with the specified phrases. The chosen keywords and the database, notably Scopus, significantly influence the scope and quality of systematic literature reviews. Scopus-based reviews employ carefully selected keywords to pinpoint thematic clusters and research trends, as demonstrated in the expert retrieval analysis, where the co-occurrence of keywords highlighted the development of themes in expert retrieval systems research [32]. Likewise, in the environmental sector review, precise keyword usage in Scopus facilitated the identification of publications pertinent to analyzing the impact of economic sectors on emissions [8].

The third selection method utilized traditional filtering techniques in a spreadsheet (Excel software). This process is depicted in Fig. 3.

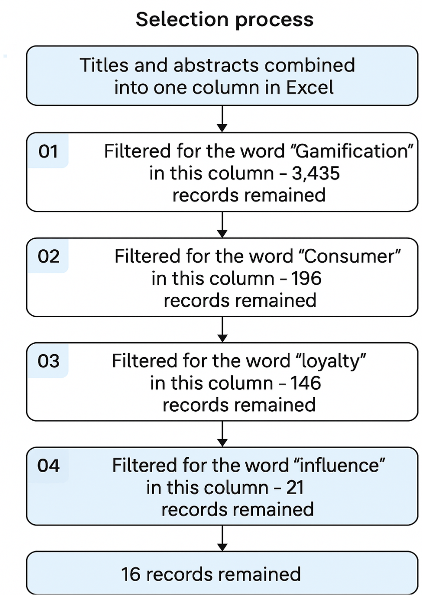


Fig. 3 The publication selection process in Excel

From the extensive dataset of 14,302 documents gathered via the query "gamification" AND "marketing," the titles and abstracts were exported and compiled into a single column. Records were filtered by identifying the presence of terms extracted by the GPT-4o model related to the main research problem: "Gamification," "Marketing," "Consumer," "loyalty," and "influence." Following several filtering steps to eliminate documents that did not match these keywords, 16 publications were retained.

A typical starting point in a keyword-based approach is to develop a precise search strategy using well-chosen keywords. In a systematic literature review, identifying relevant literature often begins with a comprehensive electronic search across various databases. Researchers then export the obtained records into Excel, a central repository for organizing and analyzing the extensive data [30]. Excel spreadsheets are designed with multiple metadata fields, including title, authors, year of publication, and abstract content, allowing for effective sorting, filtering, and comparative assessment [42]. Selecting scientific publications by keywords in Excel for a systematic literature review (SLR) consists of: crafting a strong search strategy with significant keywords, utilizing Excel as a data management tool to categorize and filter studies according to these keywords, and employing both manual and automated screening methods to improve efficiency and accuracy [14], [16], [20], [30], [42].

All three resulting sets (17 publications chosen through embedding, 15 from the refined query, and 16 from spreadsheet filtering) underwent bibliometric analysis. This analysis involved evaluating the average number of common references and keywords for each publication pair and calculating the Jaccard Index.

The arithmetic mean for each pair of publications and the Jaccard Index were utilized to assess common references and keywords. By examining the intersection (shared portion) of references between publication pairs (i,j) represented as $|R_i \cap R_j|$, where R indicates the set of references for a specific publication and n signifies the total number of publications analyzed, the average number of shared references (AR) is calculated using equation (2):

$$AR = \frac{\sum_{i<j} |R_i \cap R_j|}{\binom{n}{2}} \tag{2}$$

The Jaccard index measures similarity by taking the ratio of the size of the intersection of two sets to the size of their union. The average Jaccard Index for references (AJR) is calculated similarly to the AR for each publication pair (i, j) and then averaged as shown in equation (3).

$$AJR = \frac{\sum_{i<j} \frac{|R_i \cap R_j|}{|R_i \cup R_j|}}{\binom{n}{2}} \tag{3}$$

Likewise, the arithmetic mean and the Jaccard Index were computed for keywords using the same formulas, but the publication authors' keywords were substituted for the number of references.

The selected metrics facilitate characterizing and analyzing areas exhibiting similarity or distinctiveness. Furthermore, to enhance the reliability of the model evaluation beyond fundamental bibliometric indicators, six additional parameters were incorporated:

- The number of couples with at least one common reference: Represents the total number of article pairs with at least one bibliographic common reference.
- The number of unique references in common in at least one pair: Indicates the overall count of distinct references cited by at least one pair of articles.
- Sum of intersections (common references) for all pairs: Denotes the cumulative total of references repeatedly appearing across all article pairs.
- Number of pairs with common keywords: Reflects the total count of article pairs sharing at least one keyword.
- The number of keywords that occur together a minimum of two times: This shows the number of distinct keywords appearing in two or more articles.
- Number of articles cited in references: Counts the number of articles within the dataset cited by other articles included in the same dataset.

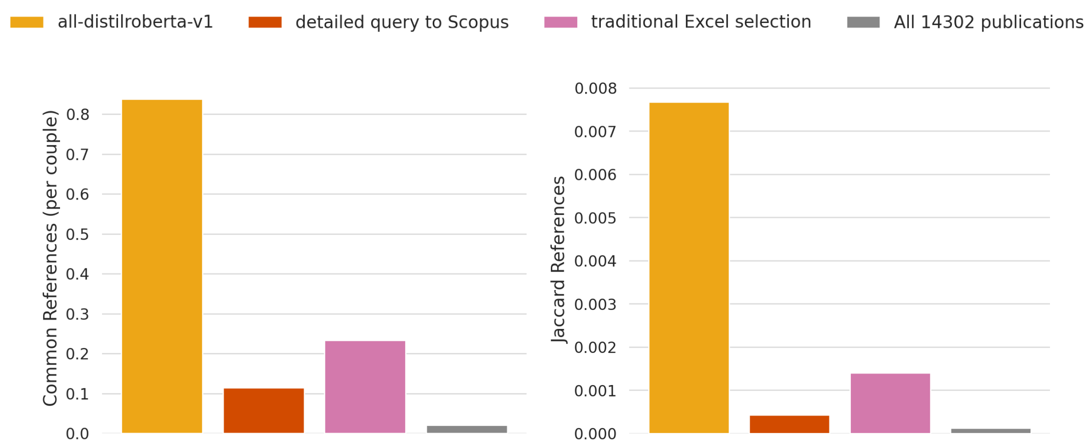
Evaluating textual data is different from classical machine learning evaluation [41]. The bibliometric evaluation focused on the average number of shared references and keywords in each publication pair, the total number of publication pairs that include at least one shared reference, and the total number of shared references across all the publications studied. Research shows that bibliometric methods, such as co-citation and bibliographic coupling, are essential in defining the intellectual framework of a research area, as they help map the academic landscape and track knowledge exchanges [15], [17], [25]. Measuring unique shared references highlights the connections between research subjects and indicates possible collaboration opportunities among researchers [5], [13].

In addition, metrics such as the Jaccard Index standardize bibliometric comparisons, allowing researchers to systematically assess the uniqueness or similarity of different literary works [33]. This methodology boosts the analysis's credibility and supports substantial discussions about research impact and theme development. Common keywords also enhance the study by offering context for the themes that arise in the literature and indicating changes in research focus over time [10].

3. Results

A comparison was made using selected bibliometric indicators of the resulting sets of scientific publications chosen by three different methods. Additionally, the obtained results were referenced against the entire, unfiltered set of publications from Scopus.

Fig. 4a and Fig. 4b illustrate the average co-reference metrics for the publication sets obtained through the three methods and the reference, complete set of 14,302 publications. The embedding-based method (all-distilroberta-v1) yields significantly higher arithmetic mean and Jaccard Index values for shared references per pair than the sets selected through a narrowed Scopus query and traditional Excel selection. This suggests a notably increased thematic coherence in the article set produced using the embedding-based method.

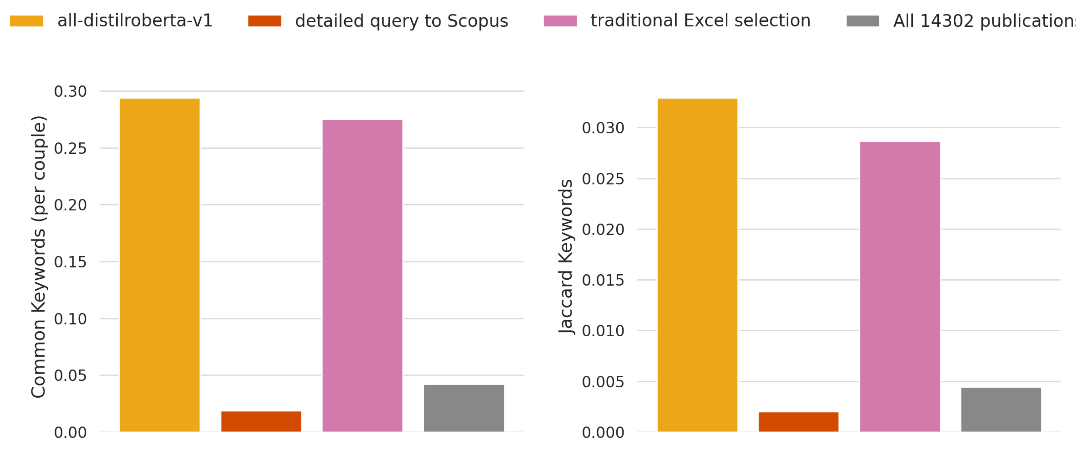


a) b)

Fig. 4. Comparison of common reference metrics for collections selected by the three methods and the reference publication set of 14,302 publications: a) arithmetic means, b) Jaccard index.

As shown in Fig. 4a and Fig. 4b, the embedding-based approach (all-distilroberta-v1) yields 17 publications with 0.84 shared references per pair and a Jaccard index of 0.0077, surpassing the 16-article Excel method (0.23 references per pair, 0.f0014 Jaccard) and the 15-article Scopus query (0.11 references per pair, 0.00043 Jaccard). For shared keywords, the embedding-based set averages 0.29 per pair (Jaccard: 0.033), compared to 0.275 (0.029) and 0.019 (0.002) for the Excel-based and specialized query methods, respectively. This indicates that the embedding-selected publications form a more cohesive thematic cluster, suggesting stronger research connections, deeper collaborative links within that subset, and stronger personal or institutional connections among the authors.

Fig. 5a and Fig. 5b compare keyword metrics from three publication selection methods and the reference publication set: the mean number of common keywords per publication pair and the Jaccard index for keywords. The method using the all-distilroberta-v1 embedding model produced a higher arithmetic mean and Jaccard index for author keywords, showcasing its superior ability to identify thematically coherent publications.



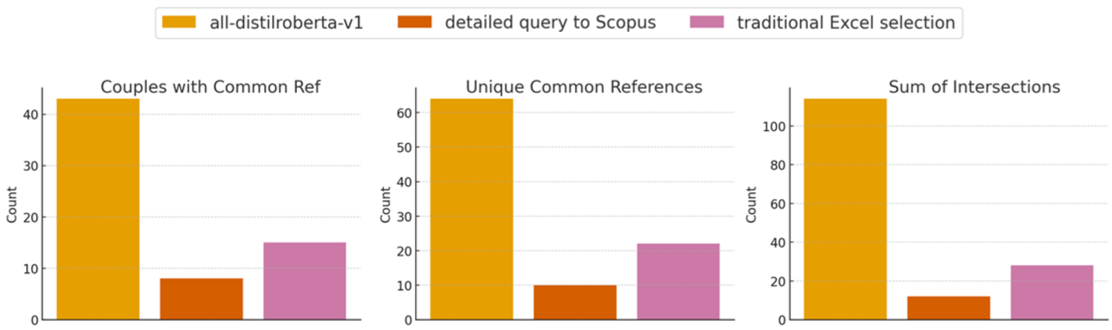
a) b)

Fig. 5. Comparison of common keyword metrics for collections selected by the three methods and the reference publication set: a) arithmetic means, b) Jaccard index.

Fig. 5a illustrates the average number of common keywords per publication pair across four groups: the 17-publication set from the all-distilroberta-v1 embedding model, the 15-publication set sourced through a comprehensive Scopus query, the 16-publication set chosen manually in Excel, and the complete reference group of 14,302 publications. Notably, the embedding-based method achieves the highest average (0.2941), outpacing the Excel-selected set (0.2750) and the Scopus-query set (0.0190). While significantly exceeding the unfiltered corpus average (0.0423).

Fig. 5b illustrates the Jaccard index for shared keywords, emphasizing the enhanced cohesion of the embedding-based set (0.03295). In contrast, the Excel selection and the Scopus query produce lower Jaccard scores (0.02865 and 0.00201, respectively), while the overall publication set reveals merely 0.00444. This indicates that the embedding-based method identifies a thematically focused set of publications, showing a closer topical overlap, as keyword metrics demonstrate clear thematic connections and similarities.

Fig. 6a, Fig. 6b, and Fig. 6c illustrate histograms that compare bibliometric indices for common publication references among datasets chosen through three different methods. The charts display results for three quantitative indicators of shared references from publications selected using an embedding-based model (all-distilroberta-v1), a comprehensive query in Scopus, and a selection made with Excel software. Due to the quantitative nature of the metric, the reference set was excluded from the analysis. The embedding-based approach identifies publications with stronger bibliometric links than the other methods, indicating its superior effectiveness in pinpointing related publications.

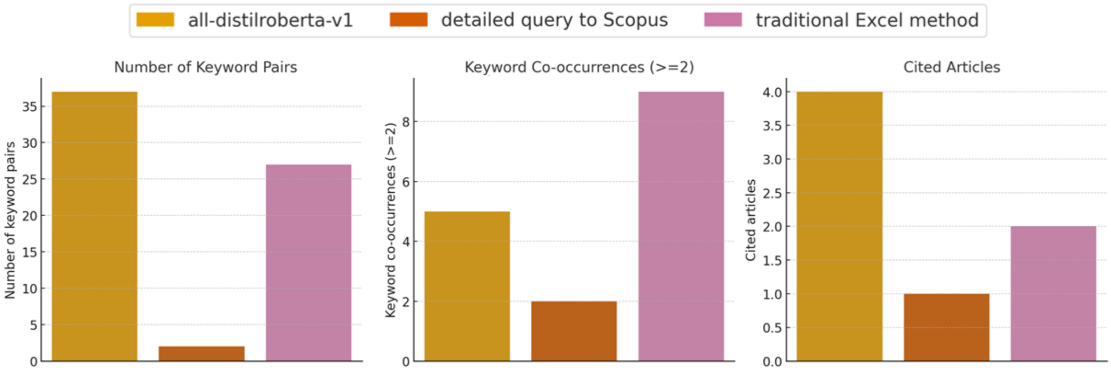


a) b) c)

Figure 6. Comparison of bibliometric indices associated with common publication references for collections selected using three methods: a) The number of couples who have at least one common reference, b) The number of unique references in common in at least one pair, c) Sum of intersections (common references) for all pairs.

Fig. 6a shows that the embedding-based method (17-publication set) generates 43 pairs with at least one shared reference, significantly exceeding the 8 pairs from the Scopus (15-publication set) and the 15 pairs from the Excel method (16-publication set). In Fig. 6b, it can be observed that this embedding-based collection also uncovers 64 unique common references, while Scopus identifies only 10 and Excel finds 22. Additionally, it boasts an average of 0.838 references per pair, significantly higher than Scopus's 0.114 and Excel's 0.233. Lastly, Fig. 6c illustrates that the embedded method yields 114 repeated citations, outpacing the Scopus set with 12 and the Excel set with 28. This highlights the superior capability of the embedding-based approach in identifying publication sets with rich bibliometric connections.

Fig. 7a, Fig. 7b, and Fig. 7c compare bibliometric indicators: the number of publication pairs sharing common keywords, the number of keyword co-occurrences (those appearing at least twice), and the number of mutual citations within the analyzed sets of articles. The results demonstrate the superiority of the embedding-based approach, which identifies publications with greater shared references, keyword co-occurrences, and mutual citations. This highlights the new method's effectiveness in detecting thematically related scientific publications, surpassing both the traditional method and the one based on narrowed search queries.



a) **b)** **c)**

Fig. 7 Comparison of bibliometric indices a) Number of pairs with common keywords b) Number of keywords that occur together a minimum of 2 times c) Number of articles cited in references

Fig. 7a shows that the embedding-based approach (all-distilroberta-v1) identifies 37 publication pairs with common keywords, while the Excel-based method yields 27 such pairs, and the narrower Scopus query finds only 2. Fig. 7b illustrates that the Excel-based approach uncovers 9 keywords that co-occur at least twice; the embedding method detects 5, and the Scopus query locates 2. Finally, Figure 7c reveals that the embedding-based set includes 4 articles cited within the references, compared to 2 for Excel and 1 for the narrower Scopus set.

This section presents a bibliometric analysis, which includes the number of shared references, common keywords, and Jaccard indices for sets of publications selected through three distinct methods, as well as for the complete reference set of 14,302 articles. The analysis demonstrates that the embedding model (all-distilroberta-v1) method produces a collection of publications with a greater quantity of shared citations and keywords, along with superior Jaccard index values compared to the other selection methods. The histograms (Fig. 6 and Fig. 7) also show that the embedding-based approach results in more publication pairs that share at least one reference or keyword, indicating enhanced mutual citation metrics.

4. CONCLUSIONS

The analysis compared three methods for selecting publications on gamification mechanisms in marketing. Particularly their effects on consumer loyalty and engagement. A novel approach utilizing an embedding model (all-distilroberta-v1) was assessed alongside traditional methods typically employed in systematic literature reviews: a refined keyword search in Scopus and manual selection via Excel. The new embedding-based method produced the best results by utilizing semantic similarity and natural language processing. This technique led to improved bibliometric indicators, including a higher count of shared sources and keywords, along with the top score on the Jaccard Index. This suggests a better thematic coherence of the selected publications.

The Excel-based selection method produced moderate results, particularly regarding keyword overlap. This confirms that manual selection can be effective, albeit less efficient, from a bibliometric perspective. The method that relied solely on narrowed keyword queries in Scopus showed the weakest results. This indicates its limited ability to capture thematically relevant literature.

The results indicate a promising potential for the proposed embedding-based selection method over traditional or solely keyword-driven techniques. These models enhance the accuracy and reliability of literature selection while significantly decreasing the time needed for systematic reviews. This implies that the proposed approach can aid in refining and automating systematic literature reviews.

However, it is essential to highlight that the comparison was solely centered on a specific topic area (gamification in marketing), thereby restricting the generalizability of its findings. Relying only on publications from the Scopus database might result in missing pertinent research from alternative sources. Sometimes the Web of Science database is also used in systematic literature reviews, so in future it would be worth extending the research to this database as well. Additionally, the cosine distance criterion utilized, which is based on vectors from the embedding model, has some methodological constraints. An undoubted limitation of this research is the use of only one all-distilrobert-v1 model. For future research, it would be beneficial to integrate multiple tools, databases, as well as to exploring and comparing different embedding models.

The implementation of these modern methods in literature selection processes can greatly benefit management and marketing research. They can increase the precision and consistency of systematic literature reviews. The study also emphasizes the importance of multidimensional bibliometric analyses in evaluating the quality of selection methods. These analyses may lead to more valuable systematic literature reviews.

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