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Medical device similarity analysis: a promising approach to medical device equivalence regulation

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ABSTRACT

Background: This study aims to facilitate the identification of similar devices for both, the European Medical Device Regulation (MDR) and the US 510(k) equivalence pathway by leveraging existing data. Both are related to the regulatory pathway of read across for chemicals, where toxicological data from a known substance is transferred to one under investigation, as they aim to streamline the accreditation process for new devices and chemicals.

Research design and methods: This study employs latent semantic analysis to generate similarity values, harnessing the US Food and Drug Administration 510k-database, utilizing their 'Device Descriptions' and 'Intended Use' statements.

Results: For the representative inhaler cluster, similarity values up to 0.999 were generated for devices within a 510(k)-predicate tree, whereas values up to 0.124 were gathered for devices outside this group.

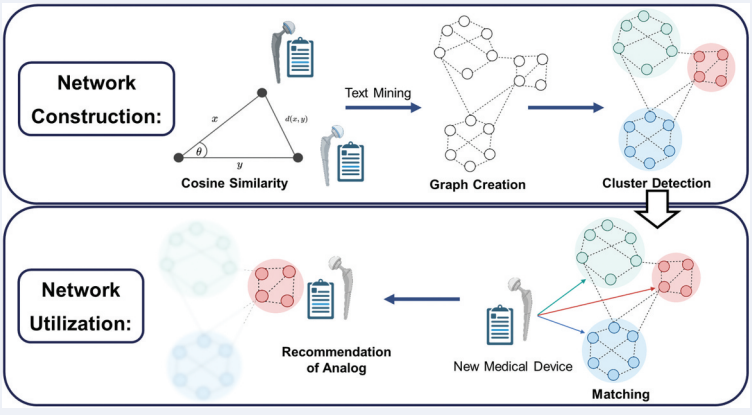
Conclusion: Traditionally, MDR equivalence involves manual review of many devices, which is laborious. However, our results suggest that the automated calculation of similarity coefficients streamlines this process, thus reducing regulatory effort, which can be beneficial for patients needing medical devices. Although this study is focused on the European perspective, it can find application within 510(k) equivalence regulation. The conceptual approach is reminiscent of chemical fingerprint similarity analysis employed in read-across.

PLAIN LANGUAGE SUMMARY

This study addresses improvement of the registration process for medical devices by using automated methods to determine how similar they are to existing devices. Such a process is already used in chemistry for analysis of related substances. In the context of Medical Device Regulation (MDR), which sets standards for these devices, this process might be applicable in device equivalence evaluation.

Traditionally, proving equivalence involves manually finding devices that are similar, but this is time-consuming, repetitive and labor-intensive. This study proposes a new approach, using advanced computer methods and a database from the US Food and Drug Administration (FDA) to automatically identify similar devices. This could make the process much quicker and more accurate and furthermore reduce bias.

The study suggests that by applying these automated methods, the impact of recent regulatory changes could be reduced. This means that proving equivalence, a critical step to facilitate device accreditation, could be done more efficiently. The study shows potential for a significant transformation in compliance processes within the medical device industry, making them more streamlined and automated.



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1. Introduction

Assessing the similarity of two entities is a highly biased and subjective procedure often performed by so-called experts. The ability to replace those by computational algorithms is considered a hallmark for modern cheminformatics [1]. This automated and unbiased similarity assessment is the initial step in analog identification and compound grouping for a read-across following the European Read-Across Assessment Framework (RAAF) [2,3]. Read-across is defined as the scientifically justified transfer of known toxicological data form a source compound to an unknown target compound. This approach for chemicals is done to avoid unnecessary testing, representing a step toward the effort of reducing the reliance on animal testing [4].

One method to compute structural similarity involves vectors, which serve as predefined and standardized sets of molecular descriptors. The similarity values are then generated utilizing different coefficients, with the Tanimoto or Jaccard index of set theory being one that is commonly used [5,6].

Comparable to chemical read-across, European device manufactures can utilize Medical Device Regulation (MDR) equivalence allowing clinical data of a registered device to enter the accreditation process of a novel one. In alignment with the principles of read-across, the ISO 10,993–18 standard defines material equivalency aiming to economizing time and costs, reducing unnecessary testing and thus saving experimental animals [7]. For MDR equivalency, applicants have to check technical, biological and clinical aspects of the device as defined in MDR, Medical Device Coordination Group (MDCG) 2020–5 and Medical Devices Documents (MEDDEV) 2.7/1 rev. 4 [8–10]. As this information is kept confidential in the technical documentation, only accessible by notified bodies, an expert panel and the manufacturer, this creates a dilemma for competing companies. Nonetheless, the first step of demonstrating equivalence involves the identification of similar devices. As the first steps of both read-across and medical device equivalence involve a grouping approach, these processes are comparable in their initial stages. According to current practice, this is accomplished in a manual, repetitive and labor-intensive procedure [11]. Similar to the European market, applicants for the US market can demonstrate 'substantial equivalence' to an already marketed predicate device utilizing the US Food and Drug Administration (FDA) 510(k) program, to which most medium risk class II devices are subjected to. Demonstrating substantial equivalence involves a comparative analysis, including aspects such as 'Intended Use' and 'Device Description' statements [12–14]. Details on the requested information within this recently digitalized process can be found on the FDA homage and related guidance documents [15]. This information is systematically documented and stored in the 510(k) database. Devices of higher risk class III undergo the standard Premarket Authorization (PMA) and relevant information are stored in the PMA database.

In this study, we developed a conceptual approach and performed a proof of concept of medical device similarity coefficients. This approach facilitates the identification of medical device analogs and thereby streamlines equivalence assessments under MDR and 510(k). The concept of medical device equivalence, which can have critical implications as highlighted by various authors [16–21], is not part of this paper and will not be discussed. This was achieved by applying distributional semantics to generate text similarities values utilizing the FDA 510(k)-database, highlighting the need for publicly available medical device information for the European market.

2. Methods

2.1. Dataset

The dataset utilized in this study comprises a comprehensive selection of up to 115 medical devices randomly sourced from the FDA medical device databases. The extraction process involved retrieving critical information for all medical devices, including manufacturer's details, device descriptions and intended use statements. Depending on the devices' risk-class, 501(k)- or PMA-numbers served as identification, starting with a 'K' or a 'P,' followed by a six-digit number.

The dataset was constructed by targeting distinct categories of medical devices. These categories comprise a diverse range of medical equipment, notably including 'Inhaler Nebulizers,' crucial for respiratory health; 'Cochlear Implants,' aiding auditory function; 'Intraocular Lenses (IOL),' vital for ophthalmological treatments; 'IOL Systems,' focusing on aiding in intraocular lens application and implantation; 'Total Hip Prostheses,' important for orthopedic interventions related to hip joint impairments; and 'Total Shoulder Systems,' integral for restoring hindered shoulder function. The device categories were selected based on and to complement the demonstrator devices within the EU Horizon 2020 MDOT (Medical Device Obligations Taskforce) project.

The dataset underwent preprocessing to refine and standardize its content for simulations. Stop words, contractions, punctuation, repeating characters, numbers, extra spaces, special characters like '®,' and potential URLs were removed. Additionally, a synonym map was applied to unify synonymous terms. This meticulous process was automated and took a few seconds to complete, making it practical for real-world applications. The result was a cleaner, more uniform dataset, ready for accurate analyses and simulations.

2.2. Computing of similarity values

Methodologically, our paper adopts a principled approach rooted in distributional semantics, analyzing the similarity between medical devices based solely on their descriptions and intended use [22], as depicted in Figure 1. The distributional hypothesis posits that words employed in similar contexts are likely to convey similar meanings [23], which is operationalized through the application of Latent Semantic Analysis (LSA).

The initial step involves choosing the focal point for analysis: either the 'Device Description,' 'Intended Use,' or a combination of both elements. Secondly, to ensure consistency and accurate comparisons, we preprocessed the textual data by employing lemmatization. This essential step

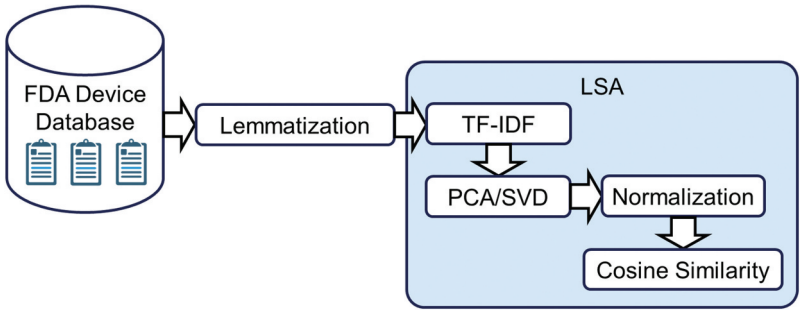

Figure 1. Semantic representation of latent semantic analysis (LSA) modeling and similarity value generation steps. Data was gathered from FDA device databases. After lemmatization, LSA is performed. Here data underwent Term Frequency-Inverse Document Frequency (TF-IDF) to generate weighted vectors. To reduce the dimensionality, Principal component analysis (PCA) or singular value decomposition (SVD) was performed. Finally, after normalization, the cosine similarity was computed.

transforms words into their base forms, unifying variations that arise from different verb forms or word endings [24].

Thirdly, the lemmatized text undergoes transformation using Term Frequency-Inverse Document Frequency (TF-IDF) [25,26]. TF-IDF contains two main components, on one hand the term frequency measures the frequency of a term within a specific document. It provides an indication of how often a word appears in relation to the total number of words in that document. On the other hand, Inverse Document Frequency (IDF), addresses the issue of common words that might be prevalent across multiple documents. IDF computes the rarity of a term across the entire corpus. When TF and IDF are combined a weighted vector representation of the document is generated, where words that are both frequent within the document and rare across the corpus receive higher weights. Conversely, common words that appear in many documents receive lower weights.

Fourthly, considering the high-dimensional nature of the resulting vectors after TF-IDF, we employed dimensionality reduction techniques, specifically Principal Component Analysis (PCA) [27] and Singular Value Decomposition (SVD) [28]. While the latter is the more canonical version within LSA, we evaluated both techniques to analyze their replicability.

Fifthly, we employed normalization which becomes pivotal after dimensionality reduction to standardize the results to later compute the similarity between medical devices. Lastly, we utilized the cosine similarity metric to evaluate the similarity between the devices. The output of the cosine similarity ranges between −1 and 1, where 1 signifies maximum similarity, 0 represents no similarity and −1 indicates inverse similarity.

After conducting the similarity analysis between medical devices, a set of matrices is generated where each value at index 'i' and 'j' signifies the similarity between 'device i' and 'device j.' To visually scrutinize the quality of this analysis and explore potential cluster formations within the data, a network-graph representation is constructed. Here, each node in the graph corresponds to a medical device, and connections between nodes are established based on the similarity values obtained from the matrices.

To maintain visual clarity and prevent an overly dense structure, connections between nodes are limited. Only medical devices exhibiting a similarity above 0.65 (65%) are linked in the graph. We empirically found this value optimal.

Subsequently, employing the Louvain algorithm becomes instrumental in clustering the generated graph [29]. Thereby, insights into potential clusters within the dataset based on text-based similarity are uncovered.

2.3. Computation of cluster metrics

We employed a Fruchterman-Reingold-algorithm [30] to display force-directed graphs. In addition, robust evaluation metrics are needed. Consequently, four different metrics classified into internal and external evaluation were analyzed. Internal cluster evaluation is based on the clustering results whereas external matrices relied on true labels as a benchmark. The values displayed are the average over five runs.

2.3.1. Internal evaluation

Two widely employed metrics for internal cluster evaluation, namely the Davies-Bouldin Index (DBI) and the Dunn Index were utilized [31,32]. The DBI gauges the quality of clustering by assessing cluster compactness and separation and is defined in Equation (1):

$$Davies-BouldinIndex = \frac{1}{K}\sum_{i=1}^{K} \max_{j\neq i}\left(\frac{\text{compactness}(i)+\text{compactness}(j)}{\text{separation}(i,j)}\right) \quad (1)$$

with K as the number of clusters. Lower values indicate superior clustering, as it reflects that clusters are compact and well separated. Further, the Dunn Index is defined in Equation (2):

$$DunnIndex = \frac{\min_{i\neq j} d_{ij}}{\max_k d_k} \quad (2)$$

By taking the ratio of the minimum inter-cluster distance d_{ij} to the maximum intra-cluster distance d_k, this metric provides a comprehensive evaluation of clustering quality. A higher Dunn Index suggests both better intra-cluster cohesion and inter-cluster separation.

2.3.2. External evaluation

Purity and Entropy served as internal clustering evaluation [33,34]. Purity measures the degree to which elements in a cluster belong to the one true class or in our case device-category. It is defined in Equation (3):

$$Purity = \frac{1}{N}\sum_k \max_j \left|C_k \cap T_j\right| \tag{3}$$

where the proportions of the true class T_j within each cluster C_k for k clusters divided by the total number of data points N. A higher purity score indicates better clustering. Entropy, on the other side, quantifies the disorder within clusters. It is defined in Equation (4):

$$Entropy = -\sum_k \sum_j P_{kj} \log_2 P_{kj} \tag{4}$$

where entropy is summed up for each cluster measuring the impurity of that cluster whereas P_{kj} is the proportion of device-class j in cluster k. A lower entropy means a low-energy scenario in which intra-cluster distances are minimized, thus the entropy is lower indicating better clustering [35].

2.4. Computational environment

The models and the plotting scripts are written in Python 3.10. Inside python, we used standardized libraries for data handling, mathematical interpretation and data visualization. Among others we used: Scikit-learn 1.4.0 [36] for modeling, python-louvain 0.16 [37] and NetworkX 3.2.1 [38] for managing graph structures. The graphical representations were generated using Seaborn 0.13.2 [39], NetworkX and Matplotlib 3.8.2.

3. Results

3.1. Determination of algorithm parameter

To generate meaningful and reproducible medical device similarity coefficients, several model parameters were initially analyzed. The goal of this process is to vary the reduction method parameters as well as input values in a way that device categories form dense and distinct clusters. To assess the quality of the cluster formation, internal (DBI and Dunn Index) and external (Purity and Entropy) cluster metrices were scrutinized (see Table 1).

In terms of model input, a consistent trend is present in which the 'Device Description' leads to the overall poorest model performance. In the case of SVD 'Intended Use' performs similarly to 'Device Description' in combination with 'Intended Use,' which is referred to as 'Both.' Although, the number of detected clusters remains constant at 'n' equals 3 and 20, both the Dunn Index and DBI reveal that the combined input 'Both' yields slightly superior clustering performance. For PCA as method to reduce dimension, the trend of 'Device Description' < 'Intended Use' < 'Both' can be discerned.

Table 1. Assessment of model cluster performance. Cluster formation was analyzed using the Louvain algorithm. Davies-Bouldin Index (DBI) and dunn Index were utilized as internal cluster evaluation. Clustering is optimal when lower DBI and higher dunn Index values are computed. Purity and entropy served as external clustering performance measure. Higher purity and lower entropy indicates better model performance. For PCA (principal component analysis) and SVD (singular value decomposition) respectively, the details of the best clustering performance are shown in the right column. 'Both' indicates a combination of 'intended use' and 'device description' as input statements. All values are averaged over 5 runs.

Model Input	Components for reduction model	n = 3	n = 10	n = 20	Details of best cluster:
Reduction model: SVD					
Intended Use	No. of clusters	3	3	5	• Reduction Model: SVD
	BDI	0.419	0.912	1.306	• # Components: 20
	Dunn Index	0.493	0.312	0.422	• Data: Both
	Purity	0.631	0.786	0.9	• Cluster Results:
	Entropy	0.921	0.651	0.2	• Inhaler Nebulizer: 20
Device Description	No. of clusters	3	3	3	• Total Shoulder Systems: 15
	BDI	0.594	1.401	1.817	• Cochlear Implants: 10
	Dunn Index	0.088	0.347	0.557	• IOL Systems: 13, Intraocular Lens: 13
	Purity	0.685	0.631	0.631	• Total Hip Systems: 40
	Entropy	0.975	0.968	0.921	
Both	No. of clusters	3	4	5	
	BDI	0.345	1.094	1.355	
	Dunn Index	0.521	0.449	0.540	
	Purity	0.631	0.693	0.9	
	Entropy	0.921	0.722	0.2	
Reduction model: PCA					
Intended Use	No. of clusters	4	4	4	• Reduction Model: PCA
	BDI	0.470	1.025	1.540	• # Components: 10
	Dunn Index	0.317	0.569	0.620	• Data: Both
	Purity	0.820	0.833	0.833	• Cluster Results:
	Entropy	0.532	0.479	0.479	• Inhaler Nebulizer: 20
Device Description	No. of clusters	4	3	4	• Total Shoulder Systems: 15
	BDI	0.587	1.404	1.693	• Cochlear Implants: 10, IOL Systems: 13, Intraocular Lens: 13,
	Dunn Index	0.075	0.298	0.381	Total Hip Systems: 1
	Purity	0.702	0.630	0.777	• Total Hip Systems: 22
	Entropy	0.780	1.043	0.627	• Total Hip Systems: 17
Both	No. of clusters	4	5	5	
	BDI	0.578	1.020	1.490	
	Dunn Index	0.246	0.497	0.333	
	Purity	0.685	0.870	0.829	
	Entropy	0.767	0.342	0.452	

Further, the number of components 'n' for reduction model was examined, and notably, for SVD, an increase in 'n' corresponds to an improvement in model performance. Contrary to that, for PCA, the clustering performance is not substantially increased from 'n' equal 10 to 'n' equal 20.

The overall best clustering performance with SVD was generated with $n = 20$ and a combined model input. In that case, as described in Table 1, five clusters are correctly identified. Just the devices within the categories of 'Intraocular Lens' (IOL) and 'IOL Systems' are not correctly separated, which can be explained by the fact that both device categories harbor devices which are functionally connected. The best results for PCA were achieved for $n = 10$. Nonetheless, the clustering performed poorer compared to SVD, as it grouped together not only 'Intraocular Lens' and 'IOL systems' but also 'Cochlear Implants' and a single hip device.

3.2. Input statements

As described above (section 3.1) the best clustering results are generated for 'Intended Use' and 'Both' as a combined input. To visually verify these results, two device categories, namely 'Cochlear Implants' and 'Inhaler Nebulizer' were assessed in separate network graphs and heatmaps. As depicted in Figure 2(e–h), 'Device Description' is not sufficient to separate the two device clusters. By contrast, as shown in Figure 2(c,d,f,g) 'Intended Use' as well as 'Both' yielded two separate device clusters. This aligns well with the clustering evaluation according to metrics.

3.3. Device search refinement

Since the objective of this study is to identify most similar devices out of large databases, it is of main interest to refine device recommendation based on regulatory considerations. This was done by implementing a filter with regulatory important information. For instance, a medical device can be of multiple or just single use. Another imported regulatory aspect is the energy consumption of a device. An active device is defined as one that depends on an external source of energy. Further, Ultra-High-Molecular-Weight Polyethylene (UHMWPE) and crosslinked UHMWPE as different medical device materials were implemented in a refined search. The number of devices after filtering based on different model input statements are shown in Table 2.

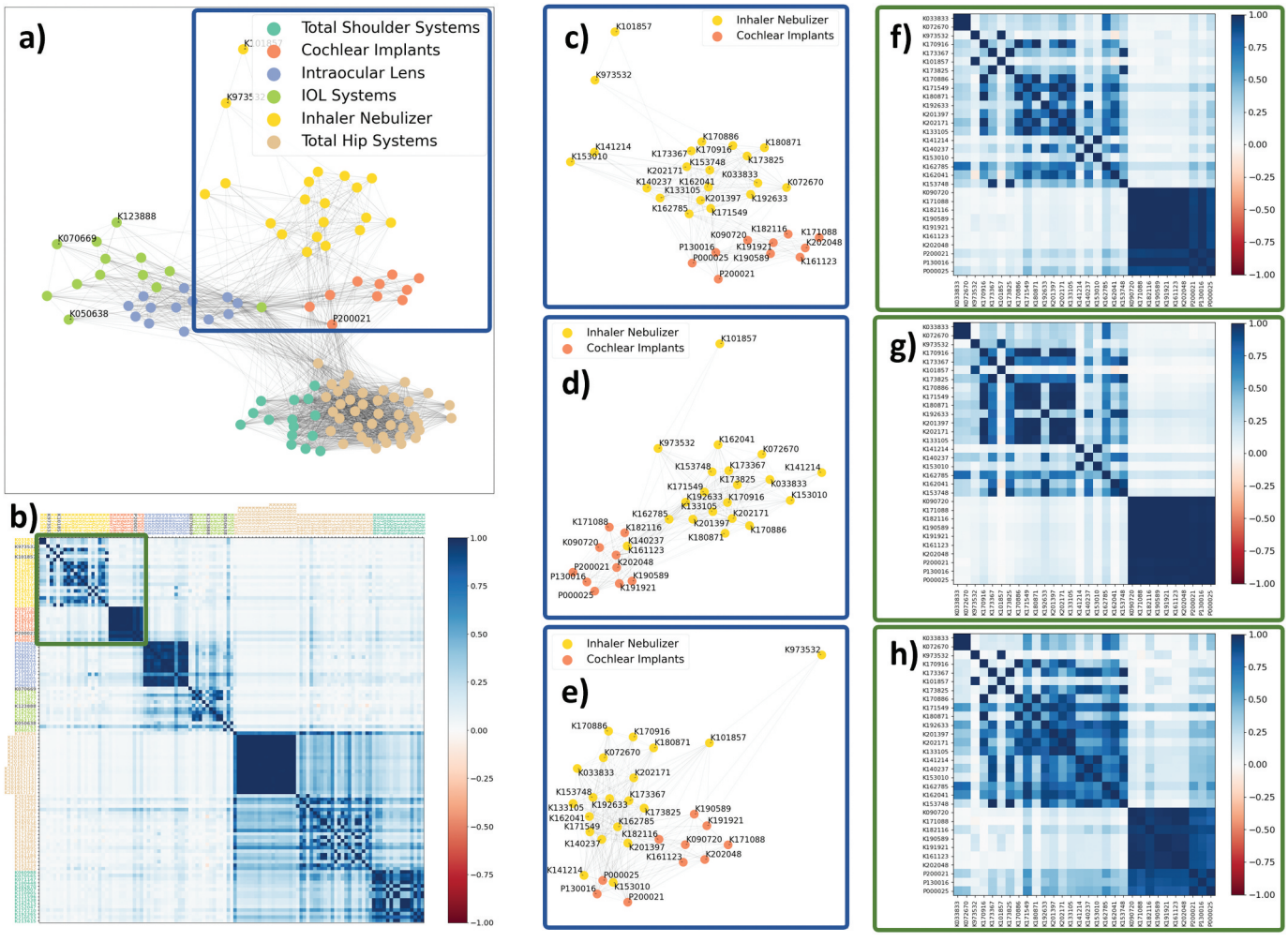

Figure 2. Input assessment of modeling algorithms. Network and heatmap based on the entire database are displayed in (a) and (b). Plots for cochlear implants and inhaler nebulizer clusters are found (c) to (h). The network representations (c), (d) and (e) are shown in the middle, whereas heatmap (f), (g) and h) are depicted on the right. Modeling input was chosen as following: (c) and (f) are based on 'both' ('device description' and 'intended use'), (d) and (g) are based on 'intended use' and (e) and (h) are generated on 'device description'.

Table 2. Results of dataset filtering. Different regulatory relevant terms, from materials e.g. Ultra-high-molecular-weight polyethylene (UHMWPE) to device classes, were analyzed based on different model inputs. The first number indicates the total number of devices that fulfill the filter requirements. Below that, device categories are listed. 'Both' indicates a combination of 'intended use' and 'device description' as input statements.

	Device Categories	Intended Use	Device Description	Both
Single Use	Total no. of devices	2	18	19
	Inhaler Nebulizer	1	4	5
	IOL Systems	1	11	11
	Total Hip Systems	0	1	1
	Intraocular Lens	0	2	2
Active device	Total no. of devices	0	12	12
	Inhaler Nebulizer	0	9	9
	Cochlear Implants	0	1	1
	IOL Systems	0	2	2
UHMWPE	Total no. of devices	0	34	34
	Total Shoulder Systems	0	7	7
	Total Hip Systems	0	27	27
Crosslinked UHMWPE	Total no. of devices	0	5	5
	Total Shoulder Systems	0	1	1
	Total Hip Systems	0	4	4

As shown in Table 2, there is a tendency that most filtering results, focusing solely on 'Intended Use' and 'Device Description,' are obtained for the latter. Therefore, 'Device Description' is to be included in our model as it provides valuable insight in the device regulatory parameters and thus is essential for refining the device recommendation. As 'Intended Use' is vital for clustering performance, the combination of 'Both' yields optimal model performance form our perspective.

To visualize the filtering-results shown in Table 3, the refined search is shown as colored and gray nodes in Figure 3. Colored nodes represent devices that match the refined search, while gray devices are filtered out. Since UHMWPE is predominantly used in hip and shoulder replacements, devices in these categories are colored in Figure 3(a). This can be refined by searching for crosslinked UHMWPE as shown in Figure 3(b). Active devices shown in Figure 3(c) are found in the clusters of 'Inhaler Nebulizers,' 'Cochlear Implants' and 'IOL Systems.' As these categories contain energy consuming devices, this is justified. The single use devices are shown in Figure 3(d) and found in several device categories, namely 'Inhaler Nebulizer,' 'IOL Systems,' 'Total Hip Systems' and 'Intraocular Lenses.' It is clear from Figure 3(c,d) that devices can meet the requirements of a single use and an active device. It became evident from the data analysis that a combination of search parameters is highly recommended for large databases in order to further refine the search result and thus find the best, potentially equivalent devices.

3.4. Internal validation

After identifying the suitable model parameter in section 3.1 to 3.3, our model is challenged by assessing the internal data structure. Although the entire dataset is used to evaluate the internal data structure, three clusters are discussed individually. For each cluster a representative device is identified (see Figure 4, blue font color) and the most similar devices are discovered (see Figure 4, green font color). Based on the network-graph one or two outliers for each cluster are found, as they are separated from the device clusters (see Figure 4, red font color). The color scheme is implemented to aid the manual device identification in Figure 4. Since our similarity values are based on the

Table 3. Cluster formation analysis after addition of external devices. Clustering performance with PCA (principal component analysis) and SVD (singular value decomposition) as dimension reduction methods were analyzed. This was done utilizing Davies-Bouldin index (DBI) and dunn index, purity and entropy as clustering metrics. Values are averaged over 5 runs. External devices in bold are associated with the clusters of devices used for model development.

	SVD, $n = 20$	PCA, $n = 10$
DBI	1.437	1.051
Dunn Index	0.403	0.245
Purity	0.809	0. 807
Entropy	0.521	0.553
Clusters containing with external devices	• Cochlear Implants: 10, Inhaler Nebulizer: 18, External Validation: 2 • Power Wheelchair • Vercise™ Deep Brain Stimulation System • IOL Systems: 13, Intraocular Lens: 13, External Validation: 1 • KARL STORZ ICG Imaging System • Total Hip Systems: 41, External Validation: 1 • ACTERA™ hip system	• Cochlear Implants: 10, IOL Systems: 1, Inhaler Nebulizer: 20, Total Hip Systems: 1, External Validation: 3 • Power Wheelchair • Vercise™ Deep Brain Stimulation System • KARL STORZ ICG Imaging System • Total Hip Systems: 23, External Validation: 1 • ACTERA™ hip system

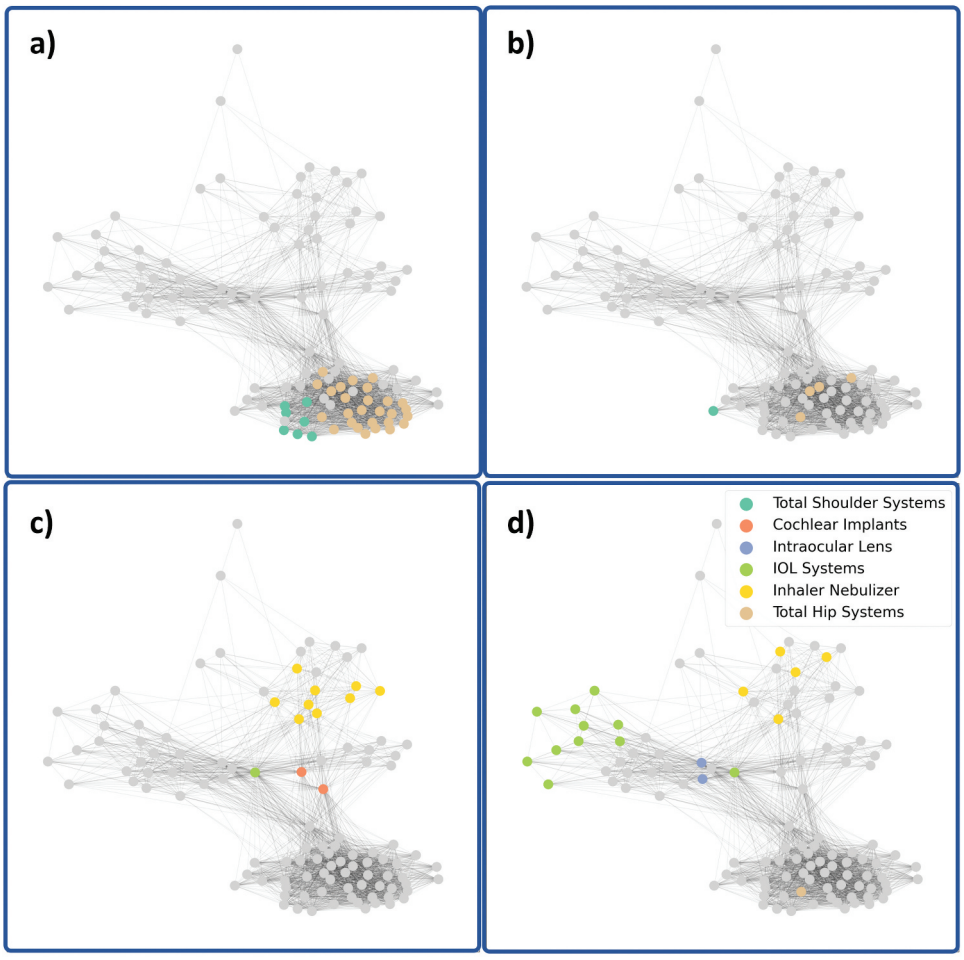

Figure 3. Visual representation of device search refinement based on regulatory aspects. Gray nodes represent devices that do not fulfill the filter requirement whereas colored nodes do. Devices are filtered by (a) ultra-high-molecular-weight polyethylene (UHMWPE) and (b) crosslinked UHMWPE to assess the utilized material, (c) active devices and (d) single use devices.

510(k) database, it is a goal to reproduce the internal FDA predicate 510(k) devices families.

3.4.1. *Internal data analyses for the hip cluster, displayed in* **Figure 4(a)**

After a check for highest similarities within the data matrix for the query device K191936 (iNSitu Total Hip System), three most similar devices (K161184: 0.991, K172501: 0.989 and K192071: 0.983) were identified. All four devices are total hip replacements. Because the query device (K191936) was registered with K161184 and K172501 as primary predicate devices, these high similarity values are justified. In addition, K192071 utilized the same predicate devices (K161184 and K172501), which explains its similarly high value.

With a similarity of 0.621 the device K210998 (ROSA® Hip System) served as an outlier. As it functions as a fluoroscopic guidance system for surgeons to aid the placement of hip implants, and is not a hip implant in itself, this is justified.

3.4.2. *Internal data analyses for inhaler and nebulizer cluster, displayed in* **Figure 4(b)**

After a check for highest similarities within the data matrix for the query device K180871 (Portable Nebulizer): three devices were identified: 0.999 for K170916, 0. 982 for K170886 and 0.960 for K202171 as all four devices utilize low-frequency vibration to create aerosol. K170916 is the predicate device for K180871 justifying 0.999 as a similarity value. In addition, K170916, K170886 and K202171 have the same predicate device (K062263) and although that device is not included in the database, the high similarity of those devices groups them together.

K973532 (Stealth, Metered Dose Inhaler (MDI) Spacer without Integral actuator) with a similarity value of 0.124 served as one of two outliers for the inhaler and nebulizer cluster. As unique feature, it aids patients with orientation and coordination problems, and thus the spatial separation is justified. In addition, K101857 (RTC 24-VP Metered Dose Inhaler Adapter) with a similarity value of 0.161 is also found outside the cluster and is the only device for intermittent delivery of aerosol medication within the dataset.

3.4.3. *Internal data analysis for the IOL system cluster, displayed in* **Figure 4(c)**

The check for highest similarities within the data matrix for K212039 (CLAREON MONARCH IV IOL Delivery System) revealed four devices as most similar. The predicate device

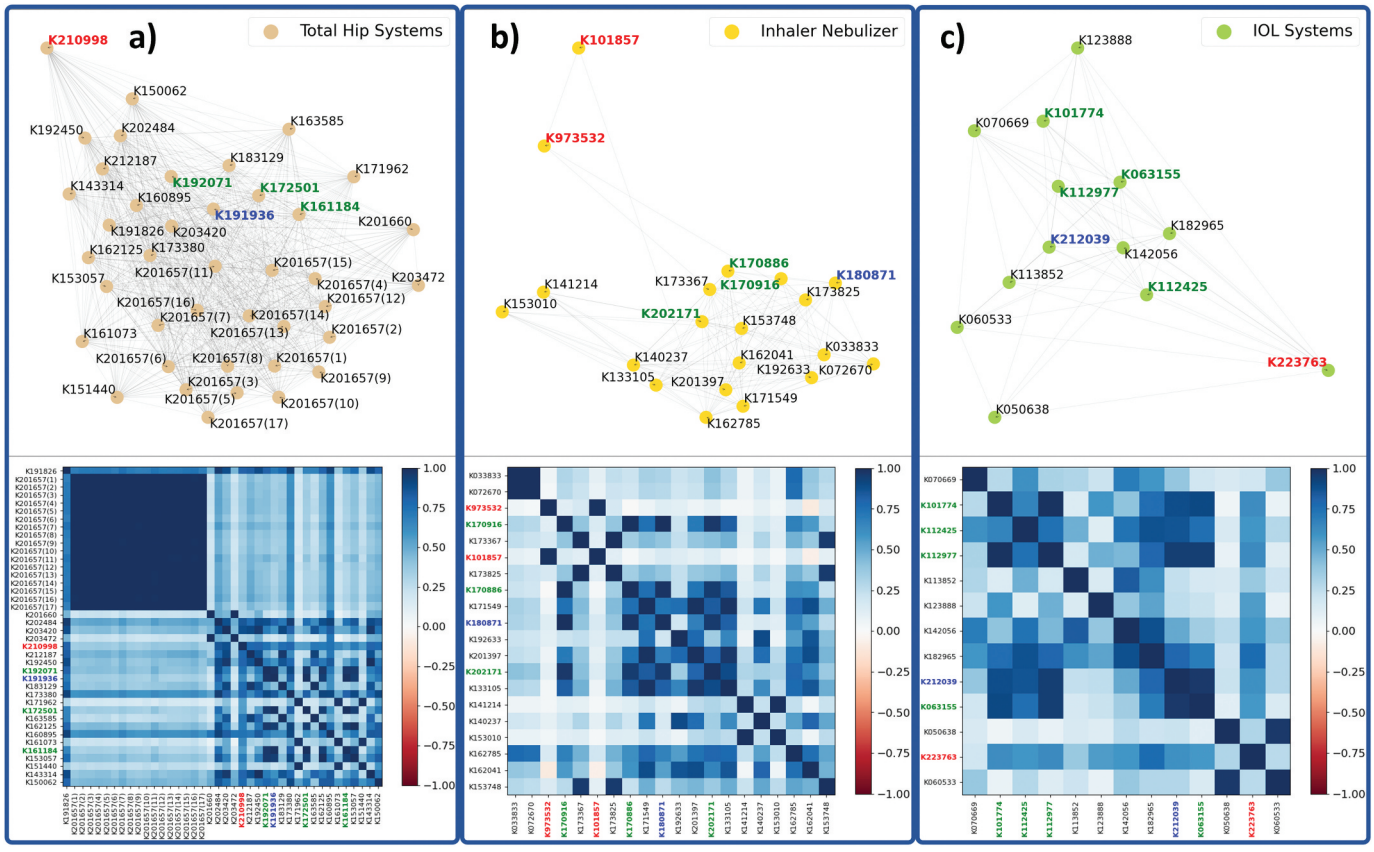

Figure 4. Evaluating cluster formation to identify outliers and validate the internal data structure. Exemplary outliers are labeled in red. To assess the internal data structure, a query device (blue) and the most similar devices (green) were analyzed. This was done for (a) the Total Hip System cluster, (b) the inhaler nebulizer and (c) the IOL System cluster. As parameter, the optimal SVD data output was chosen.

(K112977) has a similarity of 0.944, which itself utilize K063155 (0.966) as a predicate device. Further two devices (K101774, 0.889 and K112425, 0.861) were identified as highly similar to K212039, which can be justified, as they use K063155 as the predicate device and thus are grouped together.

One device within this cluster, namely K223763 (ZeptoLink IOL Positioning System), with a similarity value of 0.606, served as an outlier. As it integrates ultrasound, which is predominantly used within nebulizer systems, it is pulled out of the cluster and is thus found as an outlier. Additionally, it the only device able to perform capsulotomy.

3.5. External validation

To execute an external performance challenge, a scenario was created in which four new 'external devices' are added to the dataset. One new hip prothesis, namely K231178 (ACTERA™ hip system) was added to assess the clustering performance to preexisting device categories. Moreover, three 'external devices' do not match the established device-groups. Nonetheless, P150031 (Vercise™ Deep Brain Stimulation System) is remotely related to cochlear implants and thus should be associated with that cluster. The last two devices, K231508 (Power Wheelchair) and K232857 (KARL STORZ ICG Imaging System) are not related to any device cluster.

The clustering performance and details with these 'external devices' are listed in Table 3. Clustering performance does not significantly differ between PCA or SVD. Both reduction models showed in case of the external hip device (K231178) a correct clustering and aligned that device within the hip group. For PCA, all three remaining external devices cluster together with 'Cochlear Implants,' 'IOL Systems' and 'Inhaler Nebulizer,' which is not a good match and does not reveal any internal structure. Contrary to that, cluster performance with SVD as the dimension reduction procedure was improved. The imaging device (K232857, KARL STORZ ICG Imaging System) was clustered with devices that are related to optics, in that case 'Intraocular Lens' and 'IOL Systems.' The deep brain stimulation device (P150031, Vercise™ Deep Brain Stimulation System) is grouped with 'Cochlear Implants' and as both device categories harbor nervous tissue stimulation functions, this appears justified. Lastly, the powered wheelchair (K231508) is clustered within the same group, which includes other electrically powered devices and thus serves as the most similar group within the dataset.

To visually validate the clustering procedures, the results are analyzed as network graphs. As depicted in Figure 5(a) SVD manages to separate the four 'external devices.' The hip system (K231178, ACTERA™ hip system) is clearly associated with the other hip systems and the brain stimulation device (P150031, Vercise™ Deep Brain Stimulation System) is placed

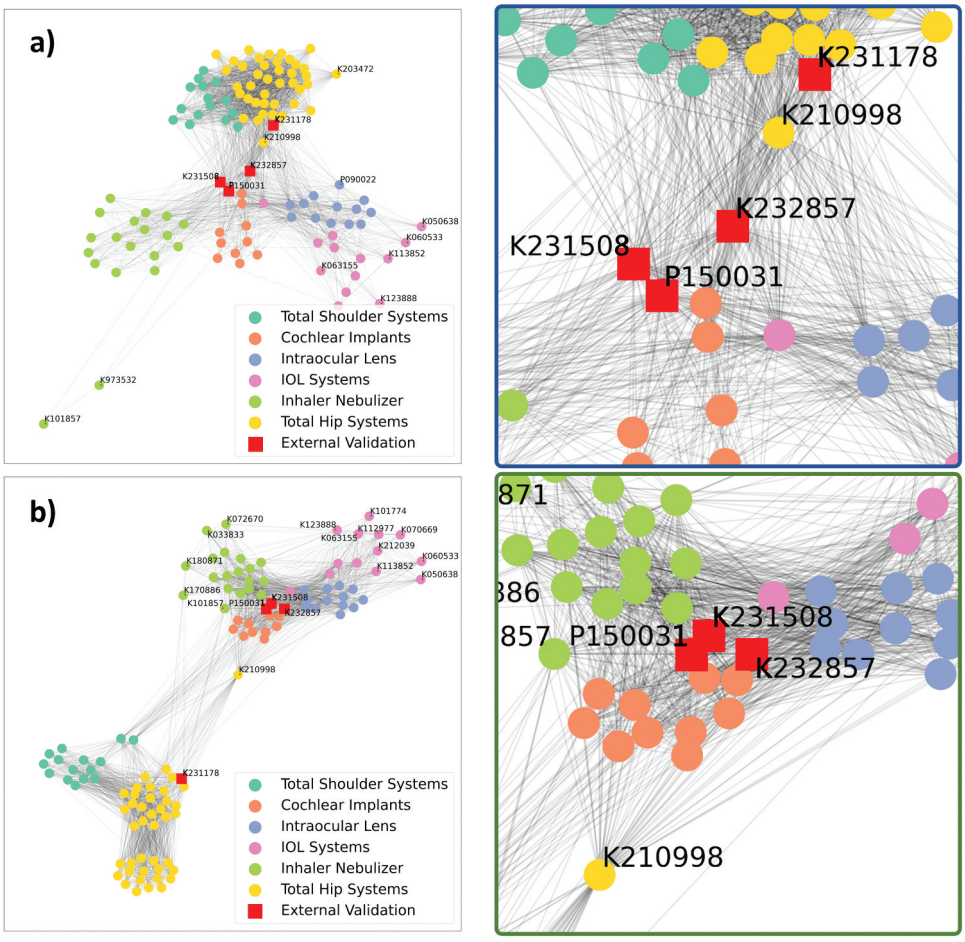

Figure 5. Spatial network orientation of externally added devices compared to the established dataset. a) SVD and b) PCA respectively served as the dimension reduction algorithm. External devices are assigned with a square node shape.

next to the cochlear cluster. The position of the powered wheelchair (K231508) in the vicinity seems to be slightly influenced by powered inhalers and the imaging device (K232857, KARL STORZ ICG Imaging System) is placed among all clusters.

A comparable spatial separation of the 'external devices' is not achieved with PCA as dimension reduction method, as displayed in Figure 5(b). Nonetheless, the hip system (K231178, ACTERA™ hip system) is clearly displayed within the other hip systems as indicated by the outcome of the clustering indices while the orientation of the other nodes is comparable to the description for the SVD graph above in spite of the fact that the individual clusteres are hardly separable.

4. Discussion

With this work we introduced a text similarity driven medical device recommendation to identify potential MDR and 510(k) equivalent devices. Our approach not only generated similarity values but allows to refine device recommendation based on regulatory parameters. The employed methods, model parameters and the relationship of device similarities to chemical similarities as well as data availability is discussed below in section 4.1 to 4.6.

4.1. Related work

The automated computation of similarity coefficients for medical devices, as discussed in this paper, aligns with the broader trends in utilizing computational techniques for healthcare-related analyses. According to Kalyan and Sangeetha, our work uses 'Online Medical Knowledge Sources' as text corpus, since amongst others the FDA database contains medical definitions and is written in professional language with free access [40]. Following the definition of Kalyan and Sangeetha, this work uses 'Document Embeddings' as embedding type [40].

A lot of work is done in the field of patient similarity evaluation. A review of different patient similarities approaches and application is found in [41], which utilizes, comparable to this paper, the cosine similarity. The work of Lee et al. set foundation of cosine similarity within patient assessment [42].

Building upon this paper's focus, Huang et al. explore the utilization of word embedding models, particularly word2vec, for representing medical terms, amongst which medical devices are found [43]. That paper's emphasis on distributional semantics and text similarity coefficients finds resonance with our work.

The concept of natural language processing (NLP) has been recently applied in a study [44] to assess the definition of

medical device material biocompatibility over the past decades. It was used to generate a novel, universally applicable definition of biocompatibility.

4.2. Model performance

With this work, it was demonstrated that SVD, as the canonical dimension reduction method, outperforms PCA. Utilizing SVD, we were able to show that 20 components within the reduction model yielded the best clustering performance. Despite showing poor clustering performance, 'Device description' is crucial for device filtering. Therefore, the model should include 'Intended Use' statements which are vital for the clustering performance and 'Device description' beneficial for filtering. It should be noted that the filtering is just as good as the input statements are. If the medical device material is not explicitly mentioned, the device is excluded. Thus, a manual review of recommended devices, filtered and unfiltered is advised. It might be beneficial to combine filtered and unfiltered device search to not miss potential best suited devices for equivalent demonstration.

Our model's BDI and Dunn Index utilizing the best model parameter, outclasses the one of Huang et al. [43]. Their mean DBI for medical terms, containing medical devices, was best at 4.282, which is about three times the DBI value of our model. Further, the optimal Dunn Index by Huang et al. was computed to be 0.4336, whereas ours at 0.540 was 25% better. The substantial difference in DBI indicates that our overall model performance is superior. However, the lowest intra-cluster and highest inter-cluster distance is comparable between our work and the clustering performance of Huang et al., indicated by the Dunn Index. This can be explained by the fact that Huang et al. implemented 2332 terms, which were selected from PubMed in an unsupervised manner.

4.3. Similarity

According to Safizadeh et al. [45] currently utilized molecular fingerprints, used to compute chemical similarities, contain a couple of hundreds to close to hundreds of thousand molecular features. These, often predefined fingerprints, have a domain of applicability, the subset of compounds, in which its performance is optimal. Opposing to that, the LSA model generates vectors, and each model runs, these vectors are calculated on the fly, thus the model's domain of applicability is expanded at the moment novel devices are introduced.

Starting in 1974, a continuous endeavor to improve fingerprint analog compound identification was set up by Cramer et al. [46]. The researchers applied a weighting scheme to the fingerprint similarity search, based on the influence of substructure on the overall compound activity. The next milestone was achieved by Arif et al., who performed a weighting based on substructures frequency [47]. These frequency weighted fingerprints outperformed the standard unweighted approach. This is comparable to the TF-IDF frequency screening of the LSA models generating word-frequency weighted vectors to generate device similarity values.

To refine the search for analogs, structural alerts are used to exclude certain compounds. Structural alerts are known substructures associated with certain toxicological modes of action. Therefore, if a compound analog contains such a structural alert, it is excluded in further drug development [48]. This approach is comparable to the filtering of medical devices implemented in this work as devices not fulfilling the filter requirements are not considered in the subsequent equivalence approach.

4.4. Equivalence based on text similarity

A lot of research went into the evaluation of universally applicable thresholds of chemical similarity. Nonetheless, over the recent years, it became clear that the computed similarity values highly depend on the utilized molecular fingerprint, the similarity coefficient and the reference compound [49]. These insights are transferable to this work since the computed device similarity values are dependent on the device under investigation.

For instance, in the internal validation, similarity values computed for representative devices found in a device equivalence hierarchy within the IOL System cluster ranged from 0.861 to 0.966. The outlier device with differing features had a similarity value of 0.606. For the inhaler and nebulizer cluster, values ranging from 0.96 to 0.999 were generated for devices within a 510(k) equivalence tree and values from 0.161 to 0.124 for the outliers.

Indicated by the high value difference of equivalent device to outlier from 0.255 in case of IOL Systems and 0.859 for inhaler and nebulizer, a universally applicable threshold for device equivalence cannot be derived. Thus, device equivalence will remain to be assessed manually in a device-by-device manner. Nonetheless, the trend that potentially equivalent devices cluster together and are well separated from devices with differing features, can be derived from our investigation. Additionally, these insights highlight that our aim to replicate the internal 510(k) data structure was accomplished as predicate device families clustered together. On the other hand, the external validation tested the algorithm's performance, which is sub-optimal if no similar devices are available within the dataset. However, the algorithm was able to identify the new hip device and clustered it correctly to the already included hip devices, demonstrating correct functionality.

4.5. EU and 510(k) device equivalence

Despite having different regulatory complexities, the European MDR and the US 510(k) device equivalence share the need for automated similarity quantification. From a manufacturer's perspective, a tool like presented in this paper could ease the search for potential equivalent devices utilizing the 510(k) database. A similar database is not available for the European market, which is discussed below. From an FDA perspective, our approach of biasfree assessing text similarity could improve the procedure of 510(k) application Thus, this tool could support manufacturers in the process of identifying potentially equivalent devices but also support the FDA in automatically assessing equivalence statements.

From the European MDR device equivalence standpoint, this approach might mitigate the labor-intensive procedure of analog device identification and thus streamline the MDR equivalence approach. Therefore, this could reduce the impact of the recently introduced MDR.

4.6. Data availability in EU

Our approach is feasible due to publicly accessible 'Intended use' and 'Device Description' statements of the 510(k)-Database. Although the EU has recently established a medical device database (Eudamed), comparable information about individual devices is not publicly available. Access to the technical documentation, containing all relevant information, is limited to the manufacturer, an expert panel and the notified body. This data policy of the European authorities concerning medical devices data was criticized by many authors [18,20,50] and limits the applicability of MDR equivalence especially in the case of competing companies. However, device manufacturers can learn in this regard from Registration, Evaluation, Authorisation and Restriction of Chemicals (REACh) and the 'letter of access,' in which the access to chemical test data is ensured between companies.

5. Conclusion

A text similarity-driven approach for the identification of potentially equivalent devices is introduced. The proposed method not only generates similarity values but allows for effective filtering of the input dataset, enabling precise recommendations that align not only with text-based similarity but also with regulatory requirements. By streamlining the MDR device equivalence our device similarity values have the potential to facilitate device accreditation and therefore reduce the impact of the MDR. In easing regulatory complexities, the currently high European device innovation rate can be maintained, which is beneficial for all medical device patients. This is especially true in the context of an aging population. Further it was noted that the lack of publicly accessible data in the EU, other than the US FDA's 510(k)-Database, hinders the application of this approach for the European market. Consequently, there is a need to overhaul the European medical device database to store more information about individual devices. Moreover, applying this tool on the 510(k) database might help manufacturers to identify 510(k) equivalent device and FDA employees to assess equivalence statements.

Abbreviation

DBI	Davies-Bouldin Index
FDA	US Food and Drug Administration
IOL	Intraocular Lenses
LSA	Latent Semantic Analysis
MDCG	Medical Device Coordination Group
MDR	Medical Device Regulation
MEDDEV	Medical Devices Documents
NLP	natural language processing
PCA	Principal Component Analysis
PMA	premarket authorization
RAAF	Read-Across Assessment Framework
REACh	Registration, Evaluation, Authorisation and Restriction of Chemicals
SVD	Singular Value Decomposition
TF-IDF	Term Frequency-Inverse Document Frequency
UHMWPE	Ultra-High-Molecular-Weight Polyethylene

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Author contributions statement

All authors have substantially contributed to the conceptualization of this work, writing the code, interpretation of the relevant literature, as well as in drafting, writing or critically reviewing this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT and DeepL to rephrase a handful of sentences and aid with grammar and spelling. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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