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Review

Compressive Sensing for Multimodal Biomedical Signal: A Systematic Mapping and Literature Review

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Abstract

This study investigated the transformative potential of Compressive Sensing (CS) for optimizing multimodal biomedical signal fusion in Wireless Body Sensor Networks (WBSN), specifically targeting challenges in data storage, power consumption, and transmission bandwidth. Through a Systematic Mapping Study (SMS) and Systematic Literature Review (SLR) following the PRISMA protocol, significant advancements in adaptive CS algorithms and multimodal fusion have been achieved. However, this research also identified crucial gaps in computational efficiency, hardware scalability (particularly concerning the complex and often costly adaptive sensing hardware required for dynamic CS applications), and noise robustness for one-dimensional biomedical signals (e.g., ECG, EEG, PPG, and SCG). The findings strongly emphasize the potential of integrating CS with deep reinforcement learning and edge computing to develop energy-efficient, real-time healthcare monitoring systems, paving the way for future innovations in Internet of Medical Things (IoMT) applications.

Keywords: compressive sensing; biomedical signal; WBSN; SMS; SLR; IoMT

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1. Introduction

The rapid advancement of wireless body sensor networks (WBSN) technology has revolutionized healthcare monitoring applications, enabling the continuous, real-time acquisition of physiological data from patients [1]. One-dimensional (1D) biomedical signals, such as electrocardiograms (ECG) for heart, photoplethysmogram (PPG) for blood flow, seismocardiogram (SCG) for heart vibrations, and electroencephalograms (EEG) for brain waves, are crucial for monitoring and diagnosing health issues [2]. However, the substantial volume of biomedical signal data collected and transmitted by WBSN devices presents significant challenges in terms of data storage, power consumption, and transmission bandwidth. Efficient data compression techniques are essential to address these issues and facilitate the practical and sustainable deployment of WBSNs [2,3]. Compressive Sensing (CS) has emerged as a particularly promising approach owing to its ability to efficiently acquire and reconstruct signals using significantly fewer samples than traditional methods [4]. This offers a potential solution for reducing the load on data storage and transmission [5].

One particularly promising technique to address these data challenges is Compressive Sensing (CS). Unlike traditional Nyquist-Shannon sampling, which requires sampling at least twice the highest frequency component of a signal, CS leverages the sparsity or compressibility of a signal to acquire and reconstruct it from significantly fewer measurements. This paradigm shift means that instead of first acquiring a dense signal and then compressing it, CS performs both sensing and compression simultaneously during the acquisition phase. The fundamental principle behind CS relies on two main conditions: the signal must be sparse or compressible in some transform domain (e.g., wavelet, Fourier), and the measurement matrix used for acquisition must be incoherent with this sparsity basis. By exploiting this inherent signal structure, CS offers a powerful framework for reducing data acquisition time, storage requirements, and transmission bandwidth, making it highly suitable for resource-constrained environments like Wireless Body Sensor Networks (WBSN). Recent research on CS has demonstrated significant advancements in optimizing compression methods for biomedical signals [2]. Several studies have explored the use of a dynamic sensing matrix to enhance the compression efficiency of ECG signals in Internet of Thing (IoT) applications [6]. Furthermore, a self-adaptive compression ratio approach, utilizing Optimized Discrete Cosine Transform (ODCT) reconstruction, has been proposed for compressing physiological voice data [7]. Deep learning techniques are increasingly being integrated with CS to improve the performance of biomedical signal compression and reconstruction. An example is the development of a deep compressive sensing framework for ECG signals, which employs multiscale feature fusion, along with squeeze-and-excitation (SE) blocks and modified Inception and Long Short-Term Memory (LSTM) blocks [8,9]. Despite these developments, the improvement of CS methods that are more adaptive, efficient, and robust to noise and artifacts in one-dimensional biomedical signals remains an active area of research [10].

Fusion, or merging of multimodal biomedical signals, is a process that integrates diverse information from various modalities (different biomedical signal acquisition devices) [3]. Multimodal feature fusion helps to generate more robust and accurate predictions because information from different modalities (data types) complements each other [2,11]. This approach addresses the limitations of incomplete information obtained from a single modality, thereby strengthening the feature representation and enriching information within a single biomedical signal data stream [12]. Each medical signal has unique characteristics that reflect different aspects of the human body. For instance, heart rate variability exhibits both low- and high-frequency components, indicating parasympathetic and sympathetic nervous system activities, respectively. Integrating various signals can provide a more comprehensive and accurate representation than relying solely on a single signal, leading to richer and more complete understanding. Researchers are increasingly interested in combining different medical signals (multimodal fusion) to gain more comprehensive insights, as a single signal type often proves to be insufficient for differentiating diseases and their symptoms. The appropriate selection of unimodal biomedical signal data and the chosen multimodal fusion strategy are two crucial components of health and affective analysis systems, often outperforming unimodal health detection and emotion recognition systems [13].

Research on multimodal biomedical signal fusion is still in its early stages, yet several studies have already demonstrated its significance in medical research [14]. However, fusion algorithms and strategies require further refinement. Biomedical signal research can not only identify physiological diseases in living beings (humans and animals), but also psychological conditions, such as mental illness [15]. Emotions are complex phenomena that have a profound impact on the quality of life, influencing drive, perception, cognition, creativity, focus, attention, learning, and decision-making [16]. To observe a person's mental state, research continues to explore the fusion of bioelectric (such as EEG) and non-bioelectric signals (such as respiratory acoustic signals or movement data) [17]. This is because unimodal approaches are often insufficiently informative and biomedical signal fusion has been proven to increase diagnostic accuracy. Beyond these medical applications, multimodal signal fusion can be applied to Body Sensor Networks (BSN) [1]. A real-time respiration pattern diagnostic system can potentially be developed by fusing sensor data from lung sounds and cardiograms [18]. BSNs represent a revolutionary technology across various domains, including healthcare, fitness, smart cities, and numerous other compelling Internet of Things (IoT) applications, enabling a single device to monitor a vast amount of user information [19]. Multimodal biomedical signal fusion generates extremely large datasets, which necessitate effective compression methods [20]. Selecting an appropriate and effective compression technique for biomedical signal data is a key aspect of the problem addressed in this study. Furthermore, the integration of deep reinforcement learning into the compression process is crucial to ensure that no vital information within biomedical signals is lost [21].

The field of compressive sensing applied to multimodal biomedical signals presents a broad and promising scope for exploration, encompassing novel multimodal signal combinations (e.g., integrating electrophysiological signals with motion data), the development of adaptive algorithms for heterogeneous and asynchronous data streams, and the establishment of robust evaluation frameworks for combined datasets. The unique combinations and characteristics of datasets gathered from diverse modalities will yield thousands of distinctive dataset variations, each requiring different treatments. This significantly increases the probability of discovering novel findings. CS methods still offer extensive potential for development, especially in optimizing data storage, computation, and transmission when combined with Deep Reinforcement Learning (DRL) [22–24]. This study aims to provide future research analysis and identify research gaps in the current work related to one-dimensional biomedical signal compressive sensing. This analysis was based on existing methodologies, specifically using a systematic mapping study (SMS) and systematic literature review (SLR), following the PRISMA protocol [25].

The remainder of this paper is organized as follows: Section 2 outlines the methodology employed for the systematic literature review, including the article selection process and data extraction. Section 3 presents the results of our comprehensive analysis, encompassing the systematic classification of methods and a comparative performance evaluation. Section 4 discusses the key findings, identified research trends, and existing limitations. Finally, Section 5 concludes the paper and highlights promising directions for future research.

2. Methods

This section details the approach to paper extraction and literature study, encompassing both the Systematic Mapping Study (SMS) and Systematic Literature Review (SLR) stages [26,27]. As illustrated in Figure 1, the methodology was executed in two distinct phases: SMS first, followed by SLR. A Systematic Mapping Study (SMS) serves as a quantitative method designed to provide a broad overview of a specific research area. This includes examining publication demographics, identifying key contributors, understanding research trends, pinpointing promising research topics, and analyzing topic models [28–30]. The insights gained from this SMS serve as crucial inputs for subsequent SLR processes. The Systematic Literature Review (SLR) involves an in-depth examination of papers identified as relevant during the SMS phase [31]. This comprehensive methods andto thoroughly understand various research methodologies and objectives related to the topic of interest, including exploring performance metrics, identifying existing issues, analyzing proposed methods, and uncovering potential gaps in previous research concerning compressive sensing and biomedical signal fusion.

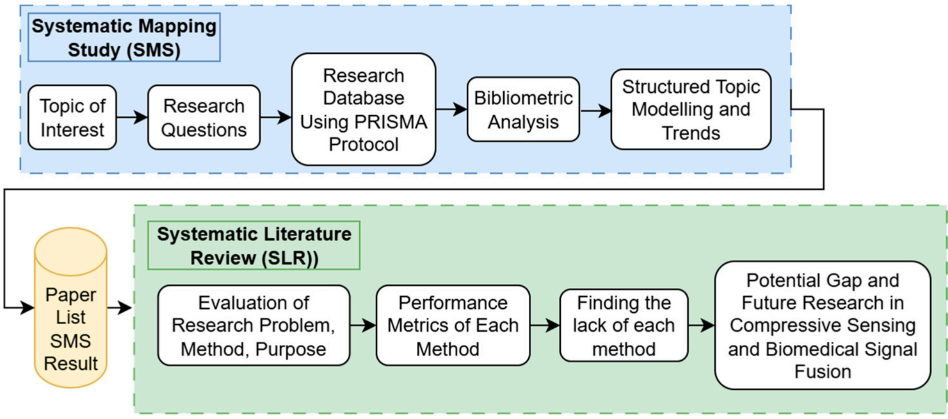

Figure 1. Research methodology.

The entirety of this systematic literature review, from article metadata collection to data analysis and visualization, was conducted using a dedicated computational environment to ensure methodological rigor and reproducibility. Metadata for the selected publications were systematically obtained from prominent academic databases, including Scopus, ScienceDirect, and IEEE Xplore. These metadata were downloaded in various formats, with CSV files primarily utilized for subsequent processing and analysis. For bibliometric analysis and network visualization, VOSviewer (1.6.20 version) was employed. Further quantitative analyses, including Latent Dirichlet Allocation (LDA) for topic modeling and subsequent statistical analyses for trend identification, were performed in Python (3.12.7 version). Key Python libraries utilized included pandas for data handling and manipulation, gensim for LDA implementation, and scipy for statistical tests. Data visualizations (such as trend plots) were generated using matplotlib and seaborn. This computational environment facilitated the systematic and reliable processing of the extensive literature corpus.

A. Systematic Mapping Study (SMS) Method

A Systematic Mapping Study (SMS) was conducted to gain an understanding of the research landscape surrounding CS and Biomedical Signal Fusion. This included identifying the latest methods or technologies from prior research and analyzing trends in topic modelling. The results of the topic model and trend analysis from the SMS process indicate that CS and Biomedical Signal Fusion constitute a promising research area.

The SMS process is illustrated in Figure 1. The initial stage involved defining the Topic of Interest and outlining the Research Questions (RQs) for the SMS. In this study, three research questions were formulated. RQ1: What is the publication population regarding CS and Biomedical Signal Fusion research between 2014 and 2025? RQ2: What areas are encompassed in this topic? RQ3: What are the trends in this topic within this subject of interest?

The subsequent stage involved paper searching, study selection, and data extraction from research databases, utilizing bibliometric analysis and adhering to the PRISMA protocol (Figure 2). Papers were searched across three prominent research databases: ScienceDirect, Scopus, and IEEE. The search query employed the keywords “Compressive Sensing Biomedical Signal” or “Compressed Sensing Biomedical Signal”. The study selection criteria included publications from 2014 to 2025, encompassing conferences, journals, books, review papers, and book chapters. The query is (title-abs-key (compressive and sensing and biomedical and signal) or title-abs-key (compressed and sensing and biomedical and signal)) and pubyear > 2013 and pubyear < 2026 and (limit-to (subjarea, “engi”) or limit-to (subjarea, “comp”) or limit-to (subjarea, “math”)) and (limit-to (doctype, “ar”) or limit-to (doctype, "cp") or limit-to (doctype, "re") or limit-to (doctype, "ch") or limit-to (doctype, "cr") or limit-to (doctype, "bk")).

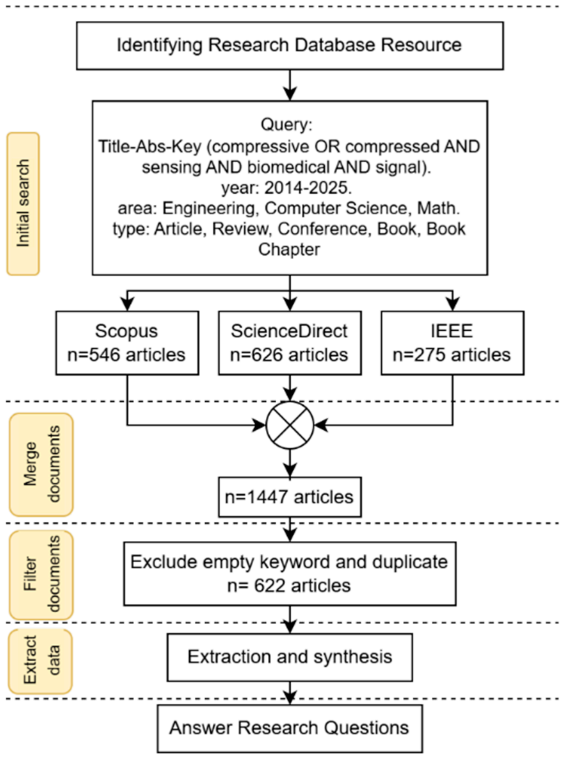

Figure 2. PRISMA protocol.

The articles were obtained from three different sources: 546 articles from Scopus, 626 articles from ScienceDirect, and 275 articles from IEEE. Following the merging of these results, a manual screening process was performed to remove duplicate titles and entries that did not contain specified keywords. This resulted in a final dataset comprising 622 articles. The last stage involved performing structured topic modelling and trend analysis, which are explained in Section 3.

B. **Systematic Literature Review (SLR) Method**

The subsequent phase of SMS involves conducting a Systematic Literature Review (SLR). The initial step of the SLR is to define the Research Questions (RQs), which comprise of the three questions detailed in Table 1. These RQs guide more in-depth research pertaining to CS problems in biomedical signals, CS parameter metrics, and biomedical signal fusion methods. Consequently, the RQs facilitate an evaluation of issues related to the methods and techniques employed in CS and biomedical signal fusion, ultimately identifying opportunities for research gaps based on the literature review conducted.

Table 1. RQs for SLR.

Research Question	Question
RQ1	What are the issues, methods, and performance metrics of CS?
RQ2	What are the limitations of existing methods in CS?
RQ3	What are the issues of CS metrics method in biomedical signal fusion?

The SLR conducts a more focused search for articles performed (from SMS) to gain a deeper understanding of CS and biomedical signal fusion. Before commencing the detailed review, articles were further explored using more specific queries, such as "CS optimization," "Adaptive CS," and "Biomedical signal fusion." The articles retrieved from this targeted search formed an augmented version of the dataset, merged with the initial SMS results, and were moved to the exclusion stage. Articles were selected from both the SMS process and the augmented set based on specific exclusion criteria, including accessibility, publication type, and content suitability. The articles that remained after this rigorous selection process were subsequently analyzed to answer predefined Research Questions (RQs). The combined outcome of the SMS and SLR analyses is the State of The Art (SOTA), which comprises key articles that serve as critical references for exploring potential research gaps and future research [32].

3. Results

The findings from both the SMS and SLR are presented in relation to their respective Research Questions (RQs). The RQs guiding the SMS will inform the results regarding trends in CS within biomedical signals, along with bibliometric analyses, topic modelling, and their corresponding trends. Conversely, the RQs of the SLR have clarified issues, methodologies, and performance metrics related to CS, identified limitations and proposed solutions, and detailed various biomedical signal fusion methods.

3.1. The SMS Result of RQ1, RQ2, and RQ3: Trend, Bibliometric and Topic Modelling

For bibliometric analysis, VOSviewer was used to construct and visualize bibliometric networks. VOSviewer is a powerful tool that aids researchers in understanding the structure and dynamics of a research field [33]. It functions by analyzing and visualizing various types of bibliometric networks, including co-authorship, citation, and co-occurrence networks. The analysis of keyword (or term) co-occurrence is central to how VOSviewer identifies topical trends. In this study, metadata from various sources, namely Scopus, ScienceDirect, and IEEE, were used and stored in the CSV file format. This data contained information such as title, abstract, keywords, authors, affiliations, publication year, references, source, and document type [34]. The threshold applied was the minimum number of occurrences of a keyword, meaning that only keywords appearing at least a specified number of times were considered in the analysis. The method used for calculating co-occurrence was Full Counting. In this method, if keywords A and B appear together in one document, they receive a score of one. If they appear in 10 documents, their score is 10. This represents a direct count of the co-occurrences. For example:

- Document 1: A, B, C
- Document 2: A, B, D
- Document 3: A, C

Then:

- Co-occurrence (A, B) = 2 (because they appear in Documents 1 and 2)
- Co-occurrence (A, C) = 2 (because they appear in Documents 1 and 3)
- Co-occurrence (B, C) = 1 (because they appear only in Document 1)

VOSviewer employs normalization techniques to calculate the link strength between keywords, because some keywords may appear more frequently in general. The formula for the Link Strength between two items (e.g., keywords) *i* and *j* is:

$$S_{ij} = \frac{C_{ij}}{W_i \times W_j} \tag{1}$$

- S_{ij} = Link strength between item *i* and *j*.

- C_{ij} = Number of co-occurrences of items i and j (i.e., how many times they appear together).
- W_i = Total weight (e.g., total number of occurrences) of item i.
- W_j = Total weight (e.g., total number of occurrences) of item j.

Figure 3 presents a visualization of research trend clustering derived from the metadata generated in the SMS. This analysis, powered by VOSviewer, served as a crucial initial step in our systematic literature review, aiming to map the intellectual landscape of compressive sensing in multimodal biomedical signals over the past decade and to systematically guide our article selection process. Based on the co-occurrence data and calculated link strengths, VOSviewer builds network. Network Visualization then displays nodes (representing individual keywords) and connecting lines (representing co-occurrence relationships) with different colors indicating different clusters. The clustering algorithm employed was based on modularity optimization, ensuring a robust identification of thematic groups.

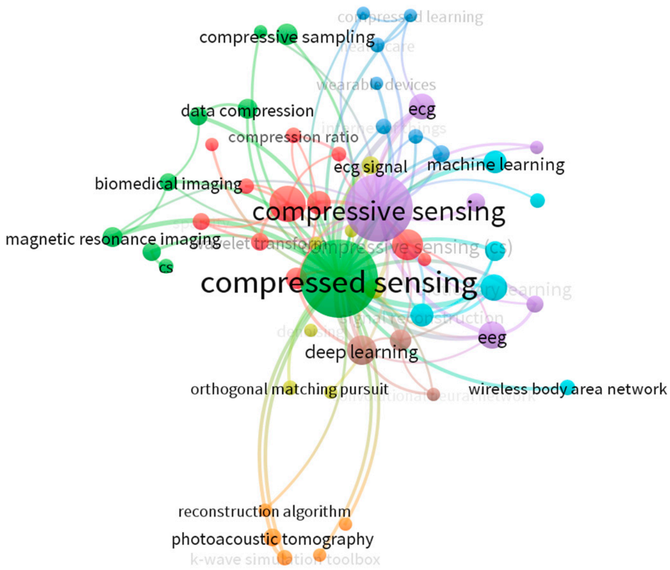

Figure 3. VOS Viewer Analysis.

This SMS contains 1436 keywords, of which 54 meet the threshold. The minimum number of occurrences of a keyword was 5. For each of the 54 keywords, the total strength of the co-occurrences link with other keywords was calculated. The visualization clearly identifies 8 distinct clusters, each represented by a different color, signifying a specific thematic area within the research domain. In this map, the size of each node is proportional to its total number of occurrences, highlighting its overall prominence, while the thickness of the links indicates the strength of the co-occurrence relationship between connected keywords, illustrating their strong thematic connections.

As observed in Figure 3, "compressed sensing" (and its variant "compressive sensing") emerges as the central and most prominent keyword, with the highest number of occurrences (168) and a total link strength of 195, unequivocally confirming its centrality to our review topic. The following keywords were used in this analysis: compressive sensing, deep learning, ECG, EEG, compressed sensing (cs), dictionary learning, electrocardiogram, signal reconstruction, classification, and so on. The clustering revealed several key thematic areas that define the field's current research fronts. For instance, the purple cluster prominently features 'deep learning', 'machine learning', and 'EEG', indicating a strong convergence of advanced computational techniques with neurophysiological signal processing. Similarly, the red and orange clusters highlight the significant application of compressive sensing in biomedical imaging, including 'magnetic resonance imaging' and 'photoacoustic tomography'. Other notable themes include specific signal applications like 'ECG' (light blue cluster) and fundamental 'reconstruction algorithms' (orange/yellow cluster). The insights gained from this VOSviewer analysis were instrumental in refining our literature selection. By visualizing the connections and thematic clusters from thousands of initial search results, we were able to validate the core relevance of our research focus, identify the most active and central sub-fields, and efficiently filter the vast corpus of literature.

In the context of analyzing author keywords from the Scopus dataset, the Structure Topic Model (STM) with Latent Dirichlet Allocation (LDA) can effectively identify research topic trends and reveal inter-topic relationships within a research publication database. As a probabilistic topic modeling method, LDA is specifically designed to uncover inherent topic structures, where each topic is characterized by a set of frequently co-occurring words grouped through an unsupervised learning approach. Critically, topic prevalence (how much a topic appears in a document) and/or topic content (words associated with a topic) can vary as a function of external covariates. Fundamentally, LDA operates under the bag-of-words assumption, treating documents as collections of word frequencies where word order is disregarded. Effective topic identification necessitates a sufficiently large corpus with diverse vocabulary, as inadequate data impedes the discovery of clear thematic patterns. Furthermore, the optimal number of topics in LDA is not automatically determined by the algorithm but rather through user experimentation. For the purpose of a systematic mapping study, STM with LDA proved to be quite powerful and capable of analyzing author keywords from a Scopus dataset to help discover patterns and topical trends [35,36]. STM models the prevalence of topics in document d as a function of document metadata X_d:

$$\theta_d \sim LogisticNormal\left(\kappa\left(X_d, \sum\right)\right) \tag{2}$$

The θ_d (topic distribution for document d) is drawn from or distributed according to a Logistic-Normal distribution of metadata X_d to the mean of the logistic-normal distribution for θ_d with covariance Σ. The results of the STM with LDA for this metadata study are shown in Figure 4.

Figure 4 shows the trends of each topic based on metadata through STM with LDA analysis. These trends are visualized using a linear regression plot, applied to the annual proportion of a topic's occurrence within the specified start-year and end-year range. Linear regression models the long-term trends of a topic's proportion within a publication database. In the graph, the blue dots represent the actual data proportion, indicating the real-time proportion of the topic in each given year. This proportion signifies the distribution of a particular topic in the Scopus dataset. For instance, a proportion between 0.01 and 0.02 suggests that approximately 1–2% of the publications in that specific year discuss this topic. If the proportion increases annually, this implies that the topic is gaining more attention in the research database. The red dashed line denotes the trend line derived from the linear regression, illustrating whether the topic's prevalence generally increased or decreased. The gray shaded area represents the confidence interval, which indicates the range of uncertainty for the regression model, thereby providing an estimate of the model's confidence in the predicted trend. The interpretation of the slope (gradient) is crucial, a positive slope indicates that the proportion of publications related to a topic increase over time. A very small slope value suggests that the topic's increase was relatively slow. Table 2 provides a comprehensive summary of the identified topics, their observed trends (trending up or down), and the explicit statistical support derived from the time-series analysis, complementing the visual representation in Figure 4.

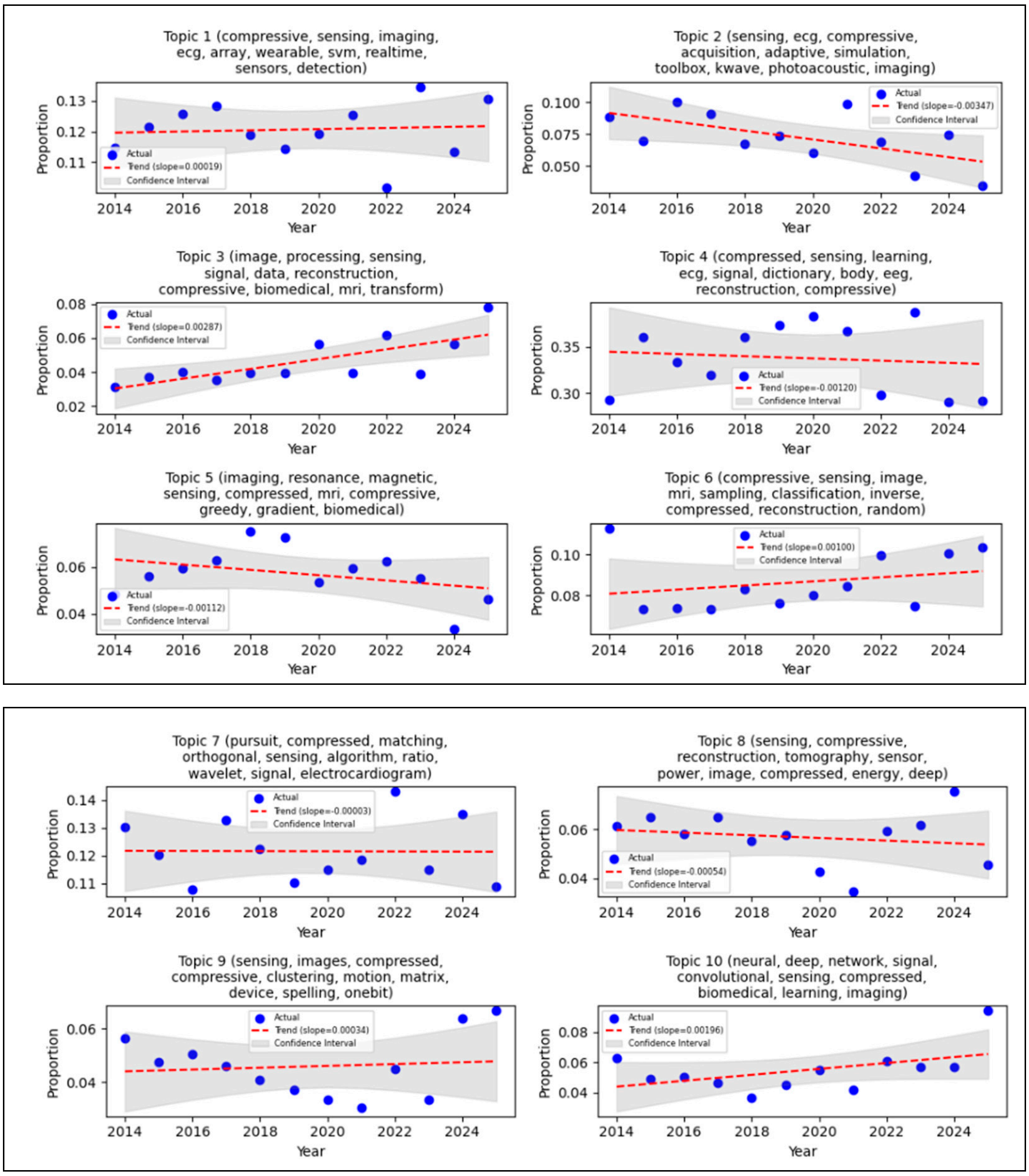

Figure 4. STM with LDA result.

Table 2. Summary of Topic Trends and Statistical Validation.

Topic No.	Representative Keywords	Mean Proportion (%)	Trend (Slope Value)	Confidence Interval (Lower Bound–Upper Bound)	Interpretation (Trending Up/Down/Stagnant)
1	compressive, sensing, imaging, ECG, array, wearable, SVM, realtime, sensors, detection	~12.0%	0.00019	~(0.105–0.135)	**Stagnant**
2	sensing, ECG, compressive, acquisition, adaptive, simulation, toolbox, kwave, photoacoustic, imaging	~7.0%	−0.00347	~(0.040–0.105)	**Trending Down**

Table 2. *Cont.*

Topic No.	Representative Keywords	Mean Proportion (%)	Trend (Slope Value)	Confidence Interval (Lower Bound–Upper Bound)	Interpretation (Trending Up/Down/Stagnant)
3	image, processing, sensing, signal, data, reconstruction, compressive, biomedical, MRI, transform	~4.5%	0.00287	~(0.025–0.075)	**Trending Up**
4	compressed, sensing, learning, ECG, signal, dictionary, body, EEG, reconstruction, compressive	~34.0%	−0.00120	~(0.300–0.370)	**Stagnant**
5	imaging, resonance, magnetic, sensing, compressed, MRI, compressive, greedy, gradient, biomedical	~5.5%	−0.00112	~(0.045–0.070)	**Trending Down**
6	compressive, sensing, image, MRI, sampling, classification, inverse, compressed, reconstruction, random	~8.5%	0.00100	~(0.065–0.110)	**Trending Up**
7	pursuit, compressed, matching, orthogonal, sensing, algorithm, ratio, wavelet, signal, electrocardiogram	~12.0%	−0.00003	~(0.110–0.135)	**Stagnant**
8	sensing, compressive, reconstruction, tomography, sensor, power, image, compressed, energy, deep	~5.5%	−0.00054	~(0.045–0.065)	**Stagnant**
9	sensing, images, compressed, compressive, clustering, motion, matrix, device, spelling, onebit	~4.5%	0.00034	~(0.030–0.060)	**Stagnant**
10	neural, deep, network, signal, convolutional, sensing, compressed, biomedical, learning, imaging	~5.5%	0.00196	~(0.035–0.090)	**Trending Up**

The more detailed analysis of Table 2 is presented in Section 4. This system provides a relevance score for article and paper titles based on a selected topic. An example of a topic search and the resulting scores are shown in Figure 5. Based on these recommended articles, titles were located within the dataset. Subsequently, the DOI or a direct link to the reference source can be retrieved to facilitate the downloading of the papers intended for Systematic Literature Review (SLR).

The systematic approach in the algorithm identifies prominent research themes within a corpus of articles, specifically by analyzing author-provided keywords. The top five article recommendations based on author keywords and topic score calculations can be found in reference number [37–41]. The initial phase involves meticulous extraction of author keywords from the dataset, ensuring the exclusion of null entries. This raw textual input then underwent a series of preprocessing steps: each keyword string was uniformly converted to lowercase, all numerical characters were removed, and punctuation was eliminated. The cleaned strings were subsequently tokenized into their constituent words, which were then reassembled into a single string.

	Title	Author Keywords	Topic Score
300	Compressive hyperspectral imaging using total ...	ADMM; Alternating direction method of multipli...	0.816990
454	Compressive Sensing of Foot Gait Signals and I...	Biomedical signals; block-sparse structure; cl...	0.804091
310	Hybrid Compression Method Using Compressive Se...	Biomedical; Biometric; CS theory; Data compres...	0.802386
389	An innovative multi-level singular value decom...	Compressed sensing (CS); Heart sounds denoisin...	0.795504
319	Exploiting wavelet decomposition to enhance sp...	biomedical imaging; compressive sensing (CS); ...	0.786338
58	Research Progress in Optical Interference Micr...	bio-optics; digital holographic microscopy; fl...	0.782058
530	Optimized nonlinear conjugate gradient algorit...	Compressed sensing; Iterative error; Liver; Ma...	0.781214
235	The accuracy and efficacy of real-time compres...	Compressive sensing; Connected health; Edge co...	0.779166
142	High-dimensional embedding network derived pri...	Compressed sensing; Magnetic resonance imaging...	0.771858
99	Compressed ECG Sensing Based Fast/Slow HR and ...	compressed ECG sensing; ECG arrhythmias; heart...	0.770578
43	Compressive sensing of ECG signals using plug-...	Compressive sensing; ECG signals; GMM denoiser...	0.770170

And others

Figure 5. Article or paper titles recommendation based on a selected topic.

Following this preprocessing, the refined text is transformed into a document-term matrix utilizing Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. This transformation assigns a numerical weight to each term, reflecting its significance in a broader dataset. For optimal performance, a maximum of 1000 unique features were retained, and common English stop words were filtered out to enhance the specificity of the extracted topics.

An LDA model was instantiated to uncover 10 distinct latent topics from the generated TF-IDF matrix. The model was then iteratively trained using vectorized textual data. To facilitate the interpretation of these discovered topics, a dedicated function extracts the top 10 most influential keywords associated with each identified topic. These keywords are precisely determined by ranking the feature names based on their respective weights within each topic's component distribution. Ultimately, the derived topics and their corresponding salient keywords were structured into a *Pandas DataFrame*, providing a clear and accessible format for subsequent visualization and in-depth analysis. This method offers a robust mechanism for inferring the primary research areas directly from author-contributed metadata.

3.2. The SLR Result of RQ1: Issue, Method, and Performance Metrics of CS

In a Systematic Literature Review (SLR), the formulation of research questions is critical for guiding the analysis and synthesis of relevant studies. The first research question focuses on three key elements: issues, methods, and performance metrics to explore emerging trends in a research topic, specifically related to the provided dataset on CS and biomedical signal fusion. Table 3 addresses the key elements by analyzing the dataset and refining the research questions.

Each methodology (in Table 3) implemented to address a specific issue is subject to performance measurement. Owing to the diverse objectives inherent to each issue, the criteria for evaluating their performance also differ. Table 4 provides a comprehensive breakdown of the performance metrics applied to each issue group, as shown in Table 3.

Table 3. Issues and Methods Related to Topic.

No.	Issue Group	Reference Number	Methods Used
1	Physiological Signal Compression (ECG, EEG, etc.)	[5–9,42–47]	• CS with Kronecker technique and full adder/subtractor design [5] • Dynamic CS for multi-lead ECG [6] • CS with self-adaptive compression ratio and Optimized DCT [7] • Deep CS with multiscale feature fusion and SE block [8] • Deep CS with modified Inception block and LSTM [9] • CS-based continuous signal acquisition with sparse group reconstruction [42] • CS compared with wavelet, spline, Gabor, and Mexican Hat [43] • Hybrid CS and classification with Walsh-Hadamard Transform, SPGL1, and CNN [44] • CS with local extrema extraction, adaptive hysteretic filtering, and LZW encoding [45] • CS with Restricted Boltzmann Machines (RBM-CS) [46] • l_2 regularized formulation of CS [47]
2	Adaptive Compressive Sensing	[10,22,48–55]	• Adaptive block CS with information entropy and synthetic features [10] • Adaptive CS with weighted iterative estimation (WIE) for WSN [22] • Compressive Adaptive Sense and Search (CASS) algorithm [48] • Adaptive CS with optimized measurement schemes [49] • Adaptive CS Radar (ACSR) with optimized waveform and sensing matrix [50] • Adaptive CS sample scheduling for WSN [51] • Adaptive rate block CS for video surveillance [52] • Adaptive block CS for target tracking in WVSN [53] • Constrained adaptive sensing with theoretical analysis [54] • Data-driven Boolean sampling matrix optimization [55]
3	Multimodal Signal Fusion for Healthcare	[3,56–58]	• Multimodal signal fusion with feature-based and decision-based techniques [3] • Feature-level fusion with linear/non-linear feature extraction, genetic algorithm, and classifiers (KNN, DT, SVM) [56] • Spatiotemporal ECG and PPG feature fusion with Choquet integral [57] • rU-Net with STFT, multi-head attention, and transfer learning for ECG and PPG [58]
4	Deep Learning for Biomedical Signal Analysis	[59–61]	• Deep Q-Learning with Deep Q-Network for EEG-based drowsiness estimation [59] • Deep learning integrated with CS for sampling and reconstruction [60] • Generalized Tensor Summation Networks (GTSNET) for CS matrix and reconstruction [61]

Table 4. Performance Metrics Related to Method and Issue Group.

No. Issue	Performance Metrics
1	• CR of 75% with reduced power consumption [5] • Compression ratio (CR) up to 16 without affecting signal metrics [6] • Percent sparsity, PRD, SNR, and power consumption for ECG/EEG [43] • CR > 15:1 with quality score for ECG compression [45]
2	• Near-optimal performance at lower SNR [48] • O(k log log(n/k)) measurements for sparse signal recovery [49] • 4.6× energy reduction, 9 dB improved image recovery [55]
3	• Higher classification accuracy than single-modality schemes [56] • RMSE of 1.49 mmol/L, MARD of 13.42%, 99.49% accuracy in Zone A + B for blood glucose monitoring [9] • AAMI standards met, BHS Grade A for blood pressure estimation [58]
4	• 2× faster reconstruction than traditional CS, improved performance at low sampling rates [60] • Improved PSNR and SSIM at low measurement rates [61]

The analysis of the identified performance metrics will be elaborated upon in Section 4.

3.3. The SLR Result of RQ2: The Limitations and Potential Research of CS

The second research question focused on the limitations of related topics and how to identify their potential research. The results show in Table 5 corresponding to the issue group from RQ1.

Table 5. Limitations and Potential Research.

Limitations	Potential Research
• Trade-off between compression ratio and reconstruction accuracy • High computational complexity for resource-constrained devices • Potential signal distortion in lossy compression • Unclear limitations in diverse IoMT scenarios • Fixed compression ratios limiting flexibility • Limited validation methods beyond neural networks	• Develop adaptive compression algorithms balancing accuracy and ratio • Optimize low-complexity algorithms for wearables • Minimize distortion in lossy compression • Evaluate dynamic CS across varied IoMT conditions • Investigate variable compression ratios • Explore alternative validation techniques
• Need for costly adaptive sensing hardware • Assumptions of Gaussian noise and feasible measurements • Complex mathematical formulations • Limited performance gains in constrained scenarios	• Design cost-effective adaptive sensing hardware • Validate performance under diverse noise models • Simplify adaptive CS algorithms • Bridge theoretical and practical benefits in constrained scenarios
• Complexity and discomfort of EEG equipment • Limited use of high-electrode EEG systems • Sensitivity to non-physiological factors • Dependence on specific datasets affecting generalizability • Limited exploration of non-audio modalities	• Develop user-friendly, low-power EEG sensors • Explore high-electrode EEG with improved comfort • Enhance model robustness to non-physiological factors • Validate on diverse datasets • Investigate visual or other multimodal stimuli
• Limited EEG dataset availability • Suboptimal EEG state design • High computational and memory demands • Limited generalizability across data types • Lack of interpretability in models • Dependence on optimal parameter selection	• Expand EEG dataset collection and synthetic data generation • Optimize EEG state design for real-world applications • Use transfer and federated learning to reduce computational needs • Validate models on varied signal types • Develop interpretable deep learning frameworks • Automate parameter optimization

This detailed analysis of the limitations and potential research directions provides a clear roadmap for future advancement in these critical areas. Addressing these identified challenges will not only refine existing methodologies but also open new frontiers for innovation in various engineering and medical applications. More analysis regarding the identified limitations and potential research of this topic will be elaborated upon in Section 4.

3.4. The SLR Result of RQ3: Methods, Limitations, and Potential Gaps in Biomedical Signal Fusion

The third research question focuses on the methods, limitations, and potential gaps in biomedical signal fusion. It is important to acknowledge its inherent limitations and to propose avenues for further exploration. These are detailed in Table 6.

Table 6. Methods, Limitations, and Potential Gaps in Biomedical Signal Fusion.

No. Issue	Methods	Limitations	Potential Gaps
1	Feature-level fusion with linear and non-linear feature extraction from EEG signals (neutral, negative, positive audio stimuli), using genetic algorithm for feature weighting and classifiers (KNN, DT, SVM) [56]	• Complexity and discomfort of conventional EEG equipment limiting large-scale data collection. • Limited use of high-electrode EEG systems (e.g., 128 or 256 electrodes) due to patient comfort and data collection challenges	• Develop user-friendly, low-power EEG sensors for large-scale data acquisition • Explore high-electrode EEG systems with improved comfort and scalability • Investigate visual or other multimodal stimuli to enhance depression recognition accuracy
2	Multimodal signal fusion categorized by signal type (physiological, medical imaging) and fusion techniques (feature-based, decision-based) for smart healthcare systems [3]	• Complexity due to the number of IoMT sensors and patients connected to the system • Challenges in data synchronization, buffering, denoising, normalization, feature selection, and decision-making (e.g., majority voting, confidence scoring)	• Implement explainable AI and interpretable machine learning to enhance fusion reliability • Explore edge-computing to reduce data transmission constraints • Develop methods to address data heterogeneity and improve synchronization
3	Spatiotemporal ECG and PPG feature fusion with three-level fusion: signal pooling, temporal and spatial feature extraction using numerical analysis and ResNets, and multi-model fusion with weighted Choquet integral [57]	• Potential limitations in wearable devices (e.g., user comfort, signal quality affected by movement, consistent sensor placement) • High computational complexity of multi-level fusion impacting real-time implementation • Limited generalizability across diverse populations due to individual physiological variations	• Enhance model robustness to non-physiological factors (e.g., stress, activity) through advanced feature engineering • Optimize computational efficiency for real-time implementation in WBAN systems • Validate models on diverse datasets to ensure generalizability

Table 6. *Cont.*

No. Issue	Methods	Limitations	Potential Gaps
4	rU-Net architecture combining U-Net and ResNet with Short-Time Fourier Transform (STFT), multi-head attention, and transfer learning for ECG and PPG-based blood pressure monitoring [58]	• Lack of implementation of wearable devices, limiting real-world applicability • Challenges in calibration effectiveness over time and optimal training data selection	• Test and optimize rU-Net models for wearable device integration • Explore improved transfer learning and calibration methods using autonomously collected datasets

This comprehensive analysis of the current methods, their inherent limitations, and the identified research gaps in biomedical signal fusion highlight critical areas for future investigation. Addressing these challenges is paramount for advancing the field, paving the way for more robust, user-friendly, and clinically impactful smart healthcare systems. A comprehensive comparative analysis, presented in Table 7, offers a more granular understanding of the current methods' capabilities and limitations in addressing these critical areas. This table meticulously outlines the characteristics, advantages, and disadvantages of key Compressive Sensing techniques, specifically evaluating their performance and design considerations regarding data storage, computational complexity, and transmission efficiency.

Table 7. Compressive Sensing Focus Areas for Optimization of Data Storage, Computation, and Transmission.

Optimization Focus Area	Method/Algorithm	Advantages	Disadvantages
Data Storage	CS for biosignal volume reduction [62,63]	Reduces massive data storage requirements (e.g., terabytes for 1000 neuron reconstruction). Enables long-term data analysis without significant information loss.	Reconstruction quality is dependent on signal sparsity, which is not always met in EEG signals. Reconstruction process can be time-consuming, especially for real-time applications.
Computation	BSBL, OMP, SOMP (for complexity reduction) [64,65]	Reduces computational load, enabling implementation on resource-constrained devices. BSBL and OMP provide accurate reconstruction with lower complexity compared to L1-norm methods.	Greedy algorithms like OMP can be less accurate for non-fully sparse EEG signals. BSBL implementation requires complex parameter adjustments for optimal results.
Transmission	CS for reducing transmitted data in wireless systems [66,67]	Reduces bandwidth requirements, crucial for long-term wireless devices. Saves battery power, extending the lifespan of wireless EEG devices.	Random matrices like Gaussian require energy-intensive operations, making them not ideal for simple hardware. Transmission quality depends on the sensing matrix design and the reconstruction algorithm

Understanding strategies for effectively integrating diverse data modalities is equally crucial, following the analysis of Compressive Sensing methods' capabilities in optimizing individual biomedical signal streams for efficient storage, computation, and transmission (Table 7). Multimodal fusion strategies determine how information from disparate sources combines, leading to richer insights or more robust decisions. A comprehensive understanding of these critical integration paradigms is presented. Table 8 offers a detailed comparison of the primary multimodal fusion strategies for biomedical signals.

Table 8. Comparison of Multimodal Fusion Strategies for Biomedical Signals.

Fusion Strategy/Level	Biomedical Signal Application	Advantages	Limitations
Early Fusion/Data Level (Raw data from multiple modalities are combined before feature extraction or modelling.) [3,68,69]	• EEG + NIRS for emotion classification • ECG + PPG for heart rate estimation • EMG + motion sensors for hand rehabilitation	• Captures cross-modal interactions early, improving predictive power. • Preserves raw data information. • Suitable for highly correlated modalities.	• High computational complexity due to large data dimensions. • Requires synchronized and compatible data (e.g., same sampling rate). • Sensitive to noise or scaling differences across modalities
Intermediate Fusion/Feature Level (Features extracted from each modality are combined before decision-making.) [3,70,71]	• EEG (spectral features) + ECG (HRV features) for sleep apnoea detection • Medical images (HOG, texture features) + EEG for disease diagnosis • EMG (time-frequency features) + inertial sensors for gesture recognition	• Reduces dimensionality compared to early fusion. • Flexible for heterogeneous modalities (e.g., signals and images). • Allows modality-specific feature extraction.	• Requires effective feature extraction methods. • May lose low-level data information. • Feature alignment across modalities can be challenging
Late Fusion/Decision Level (Decisions or scores from individual modality models are combined for final output.) [3,72,73]	• EEG + EMG for sleep apnoea classification (separate classifiers combined via voting) • ECG + SpO2 for respiratory rate estimation (weighted averaging) • EEG + eye-tracking for cognitive load assessment	• Computationally efficient as modalities are processed independently. • Robust to noise in individual modalities. • Suitable for distributed systems (e.g., IoMT with edge computing)	• Limited capture of cross-modal interactions. • Performance depends on individual model quality. • Requires effective decision combination methods (e.g., weighted voting).

This systematic comparison highlights that while significant advancements have been made in each area, trade-offs frequently exist between high compression ratios, computational efficiency, and real-time transmission capabilities. Understanding these specific characteristics, advantages, and disadvantages for each method is crucial for identifying optimal CS solutions for varied biomedical signal applications and for guiding future research towards more holistic optimization strategies.

4. Discussion

The Systematic Mapping Study (SMS) and Systematic Literature Review (SLR) conducted in this research emphasize the escalating importance of Compressive Sensing (CS) within biomedical signal processing, particularly concerning Wireless Body Sensor Networks (WBSN). A bibliometric analysis, performed using VOSviewer, revealed prominent research clusters formed around keywords such as "compressive sensing," "deep learning," and "ECG." Notably, "compressed sensing" exhibited the highest occurrence (168) and a total link strength of 195, signifying a strong research emphasis on optimizing CS techniques for physiological signals, including ECG and EEG. Furthermore, trend analysis, visually represented through Structural Topic Modelling (STM) with Latent Dirichlet Allocation (LDA), showed a positive slope in topic prevalence. This indicates a consistent surge of interest in CS applications for biomedical signals throughout the 2014 to 2025 period. This observed trend highlights CS's substantial potential to mitigate critical challenges in data compression, storage, and transmission. These are the principal factors for the development of energy-efficient and real-time healthcare monitoring systems. Figure 4 describes the STM with LDA result for topic 4 as the highest proportion of articles (approximately 35%) with author keyword combinations: compressed, sensing, learning, ECG, signal, dictionary, body, EEG, reconstruction, and compressive. Topic 9 showed the lowest proportion of articles whit stagnant trends from 2014 till 2025. Topic 3 showed the highest trend, whit a slope of 0.00287, but its proportion is still low. The negative slopes indicate that the proportion available for research or publication consequently decreases, these are topics 2, 4, 5, 7, and 8. Confidence interval estimates of the model's confidence in the predicted trend, and topic 3 had a good confidence interval for this study. This means that the number of articles (with their author keywords) has consistently increased each year.

A significant challenge identified in the SLR is the inherent trade-off between compression ratio and reconstruction accuracy, which is particularly critical for resource-constrained devices in Internet of Medical Things (IoMT) applications. For example, while approaches, such as dynamic CS for multi-lead ECG have demonstrated compression ratios of up to 16 without degrading signal metrics, their high computational complexity poses a bottleneck for integration into wearable devices. Furthermore, the incorporation of adaptive CS techniques, such as the Compressive Adaptive Sense and Search (CASS) algorithm, can achieve near-optimal performance at lower signal-to-noise ratios (SNR).

However, the dependence on costly adaptive sensing hardware restricts scalability. This "adaptive sensing hardware" typically refers to specialized analog-to-digital converters (ADCs) or front-end circuitry that can dynamically adjust measurement parameters (e.g., sampling rate, measurement matrix configuration) based on real-time signal characteristics or changing environmental conditions. Such dynamic configurability, while offering performance benefits, often leads to increased design complexity, power consumption, and manufacturing costs compared to fixed-rate, non-adaptive hardware. Consequently, future research should prioritize the development of low-complexity algorithms that effectively balance reconstruction accuracy with computational efficiency. This can potentially be achieved by leveraging hardware-accelerated implementations to minimize power consumption in WBSN deployments. The SLR results also emphasize the potential of multimodal signal fusion for improving diagnostic accuracy in healthcare applications. For instance, techniques such as spatiotemporal ECG and PPG feature fusion, augmented by the Choquet integral, have demonstrated high classification accuracy (e.g., 99.49% in Zone A + B for blood glucose monitoring), consistently outperforming approaches based on single-modality data. The practical implementation of such systems is challenged by factors including the inherent complexity of EEG equipment and its sensitivity to non-physiological factors, such as motion artifacts. Addressing these limitations necessitates the development of user-friendly, low-power EEG sensors and the creation of robust feature engineering techniques capable of mitigating non-physiological noise. These advancements have significantly enhanced the scalability of multimodal fusion systems. Furthermore, exploring edge-computing frameworks to manage data synchronization and heterogeneity within IoMT environments could further optimize real-time performance, thereby overcoming the limitations of current fusion methodologies.

The integration of deep learning with CS, exemplified by methods such as deep CS with multiscale feature fusion and rU-Net architectures, holds significant promise for improving the reconstruction performance even at low sampling rates. However, substantial barriers persist, notably high computational demands and limited generalizability across diverse data sets. These issues can be mitigated through the application of transfer and federated learning, as suggested in Table 6. Such approaches would reduce computational overhead and enable model adaptation to various physiological signal types. Furthermore, automating parameter optimization using techniques such as Deep Reinforcement Learning (DRL) can enhance the adaptability of CS frameworks, making them more suitable for dynamic Internet of Medical Things (IoMT) scenarios. These advancements will facilitate the deployment of CS-based systems in resource-constrained environments, thereby paving the way for next-generation healthcare monitoring solutions.

Building upon the identified limitations and research gaps, several critical open questions emerge, guiding future investigations in Compressive Sensing (CS) for multimodal biomedical signal processing within WBSN and IoMT contexts. These questions aim to advance the field towards more robust, efficient, and user-centric healthcare monitoring systems.

For CS optimization in resource-constrained devices, future research must develop adaptive compression algorithms that optimally balance compression ratio and reconstruction accuracy for diverse 1D biomedical signals from wearables. This includes designing novels, low-complexity, hardware-accelerated CS reconstruction algorithms to minimize computational overhead and power consumption in real-time WBSN deployments and minimizing signal distortion in lossy CS compression while maintaining high ratios for IoMT. Additionally, exploring alternative validation techniques beyond traditional neural networks is crucial to assessing the clinical utility of CS-reconstructed biomedical signals across diverse patient populations.

Regarding adaptive sensing hardware and noise robustness, a key challenge lies in designing cost-effective adaptive sensing hardware architectures that offer dynamic measurement schemes without significantly increasing complexity or power draw for continuous monitoring. Validating adaptive CS algorithms for robust performance under diverse and realistic noise models (e.g., motion artifacts, environmental noise) in real-world acquisition is essential. Furthermore, simplifying mathematical formulations for adaptive CS is needed to bridge theoretical performance gains with practical benefits in constrained clinical settings.

In the domain of multimodal signal fusion in IoMT, developing user-friendly, low-power, and scalable EEG sensors is necessary to overcome the complexity and discomfort of conventional high-electrode systems for large-scale data acquisition. Research should also focus on advanced feature engineering and model architectures to enhance the robustness of fusion models to non-physiological factors and ensure generalizability. Integrating explainable AI (XAI) and interpretable machine learning approaches into multimodal fusion systems is vital to enhance reliability and trustworthiness of diagnostic predictions. Finally, identifying effective edge-computing frameworks and strategies is crucial for addressing data synchronization, heterogeneity, and transmission constraints for real-time fusion within distributed IoMT environments.

Pertaining to deep learning integration with CS, future work should leverage transfer and federated learning to reduce high computational, and memory demands of deep CS frameworks, enabling deployment on resource-constrained WBSN nodes and improving generalizability across varied signal types. Developing novel deep learning frameworks that automate parameter optimization in CS algorithms will enhance their adaptability to dynamic IoMT scenarios. Lastly, improving interpretability in deep learning models integrated with CS for biomedical signal analysis is critical for clinical acceptance and trust. Addressing these questions will be pivotal in unlocking the full transformative potential of CS combined with multimodal fusion and deep learning, paving the way for the next-generation, ubiquitous, and clinically impactful healthcare monitoring solutions.

5. Conclusions

The findings from the SMS and SLR collectively emphasize the transformative potential of CS in biomedical signal processing, especially when integrated with deep learning and multimodal fusion techniques. Despite these advancements, significant research gaps remain in literature. These include the necessity for cost-effective adaptive sensing hardware, the development of simplified algorithms suitable for resource-constrained environments, and the crucial need for robust validation across diverse IoMT scenarios. Addressing these identified gaps by combining expertise in signal processing, machine learning, and hardware optimization will be critical for fully realizing CS's potential in revolutionizing WBSN-based healthcare systems.

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Abbreviations

The following abbreviations are used in this manuscript:

CS	Compressive Sensing or Compressed Sensing
SMS	Systematic Mapping Study
SLR	Systematic Literature Review
DLR	Deep Reinforcement Learning
EEG	Electroencephalogram
ECG	Electrocardiogram
PPG	Photoplethysmogram
SCG	Seismocardiogram
SNR	Signal-to-noise-ratios

CASS	Compressive Adaptive Sense and Search
KNN	K-Nearest Neighbors
DT	Decision Tree
SVM	Support Vector Machine
WVSN	Wireless Vehicle Sensor Network
WBSN	Wireless Body Sensor Network
IoMT	Internet of Medical Things
BSBL	Block Sparse Bayesian Learning
OMP	Orthogonal Matching Pursuit
SOMP	Simultaneous Orthogonal Matching Pursuit

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