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A Decade of Progress in Drowsiness Detection Using Facial Features: A Comprehensive Bibliometric Analysis and Thematic Mapping

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Abstract This study presents a comprehensive bibliometric analysis of research trends in drowsiness detection using facial features, examining publications from 2014 to 2024. Employing a PRISMA-guided methodology, we extracted and analyzed 347 documents from the Scopus database, revealing significant patterns in research productivity, citation impact, geographical distribution, institutional contributions, and thematic evolution. Our analysis identifies an annual growth rate of 18.59% in publication volume, with a notable surge after 2019, coinciding with the widespread adoption of deep learning approaches. Geographically, Asian countries dominate research output, with India (182 publications) and China (100 publications) leading contributions, while China garnered the highest citation impact (1370 citations). Through sophisticated co-occurrence network analysis, we identified four distinct research clusters: (1) Physiological Insights via Neural Networks, (2) Computer Vision-Based Drowsiness Detection, (3) Multi-Modal Fatigue Detection for Accident Prevention, and (4) Deep Learning for Biomedical Signal Analysis. Temporal analysis of keyword evolution reveals a shift from traditional machine learning approaches toward deep neural networks, Internet of Things integration, and real-time monitoring systems. Our thematic mapping further categorizes research into basic themes (CNNs, eye aspect ratio), motor themes (driver fatigue detection, cloud computing), niche themes (3D head pose estimation, behavioral measurement), and emerging/declining themes (pupil detection, blink detection systems). Systematic analysis of deployment metrics reveals critical gaps: only 3.3% of top-cited papers report frames per second (FPS), and none report latency or time-to-alarm (TTA), despite frequent claims of real-time capability. Analysis of multimodal approaches shows 74% of studies focus exclusively on facial features, while 26% incorporate physiological or vehicular signals. This comprehensive bibliometric landscape illuminates the field's evolution, identifies research gaps particularly regarding deployment readiness, ethnicity-specific considerations and low-light environments, and provides a strategic roadmap for future research directions in drowsiness detection systems.

Keywords Advanced driver assistance systems, bibliometric analysis, computer vision, convolutional neural networks, deep learning, drowsiness detection, driver monitoring, eye tracking, facial features, Internet of Things

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1. Introduction

Driver drowsiness detection sits at the intersection of computer vision, deep learning, and transportation safety, with direct implications for reducing crashes and saving lives. Fatigue-related crashes are frequently cited as a major contributor to road fatalities, often estimated at **20–30%** of all road deaths [1, 2]. Beyond casualties, the socioeconomic burden spans healthcare expenditure, productivity loss, and broader societal costs. As vehicular technologies advance, robust **real-time** drowsiness monitoring has become an essential building block of Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS).

Detecting drowsiness is inherently challenging. Fatigue manifests gradually, varies across individuals, and is confounded by environmental factors such as illumination, glare, and vibration. Prior work spans three broad

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modality families: **physiological signals** (e.g., EEG, ECG) [3], **vehicular dynamics** (e.g., steering entropy, lane deviation), and **behavioral/visual cues** (e.g., eye and facial dynamics) [4, 5]. Among these, **facial-feature approaches** have attracted sustained attention because they are **nonintrusive**, feasible for **real-time** deployment, and comparatively **cost-effective** relative to sensor-heavy alternatives [6, 7, 8].

Recent progress in computer vision especially deep neural architectures (e.g., CNNs and temporal variants) has enabled fine-grained modeling of fatigue-related cues: eye-closure patterns and blink rate, yawning frequency, head-pose dynamics, gaze behavior, and **PERCLOS** (percentage of eyelid closure), a long-standing proxy of drowsiness validated in early on-road studies [9, 10]. In parallel, **edge computing** and automotive IoT have matured, enabling **onboard** inference and tighter integration with in-vehicle systems, which brings laboratory models closer to deployable Driver Monitoring Systems (DMS) [11, 12].

Despite this momentum, the field lacks a **comprehensive, PRISMA-guided bibliometric synthesis** focused specifically on **facial-feature–based** drowsiness detection. While several narrative or technique-specific reviews exist [13, 14], a systematic field-level mapping covering macro trends, collaboration networks, venues, and thematic evolution remains limited. This hinders strategic planning by obscuring where research effort concentrates and where high-impact opportunities remain (e.g., low-light robustness, fairness across subpopulations, and **deployment-oriented metrics** such as **FAR/min**, **time-to-alarm (TTA)**, **latency**, **FPS**, and **power**).

Value of Bibliometric Analysis. Unlike narrative reviews that rely on subjective selection and synthesis, bibliometric analysis provides a systematic, data-driven approach to mapping research landscapes. This methodology offers several key advantages: (1) **objectivity and reproducibility**—systematic queries and standardized metrics minimize selection bias; (2) **quantitative pattern identification**—computational analysis reveals hidden trends in collaboration networks, citation dynamics, and thematic evolution that may not be apparent through manual review; (3) **comprehensive coverage**—all 347 papers meeting inclusion criteria are analyzed rather than a selective subset; (4) **temporal dynamics**—tracking of keyword evolution and citation patterns over time provides insights into field maturation; (5) **geographic and institutional mapping**—identification of research hubs, collaboration patterns, and productivity centers; and (6) **visual knowledge mapping**—intuitive visualization of research clusters and thematic relationships through network analysis. By applying bibliometric methods to drowsiness detection research, we provide the first comprehensive, quantitative mapping of this domain's evolution, complementing existing narrative reviews with empirical evidence of research trends and gaps.

To address this gap, we perform a **systematic literature review and bibliometric analysis** of facial-feature–based drowsiness detection spanning **2014–2024**. While our analysis covers an 11-year period, we use "a decade" in the title to represent approximately ten years of consolidated research progress in this rapidly evolving field. We follow **PRISMA 2020** for transparent selection and reporting to fully document the search strategy. Using established bibliometric tooling, we quantify research productivity and impact, identify leading contributors and venues, map conceptual structures via co-word and thematic analyses, and translate these signals into **actionable research directions** that support deployment (e.g., few-shot personalization on device, robustness under domain shift, and edge-oriented evaluation).

Contributions.

1. A quantitative panorama of publication and citation dynamics (2014–2024).
2. Identification of key **countries, institutions, authors, and journals**, and their collaboration structures.
3. A thematic map of predominant and emerging topics via keyword co-occurrence and thematic evolution.
4. Systematic analysis of deployment readiness revealing critical gaps: only 3.3% of top-cited papers report FPS, 0% report latency or TTA, despite 23.3% claiming real-time capability.
5. Quantitative evidence that 74% of research focuses on facial-only approaches while 26% incorporate multimodal signals, with no significant temporal trend toward increased multimodal adoption.
6. A gap analysis that surfaces **low-light**, **fairness**, and **deployment-metric** deficiencies and motivates concrete technical next steps.

1.1. Research Questions and Scope (PICOC)

Guided by the **PICOC** framework, we state the scope and research questions explicitly:

- **Population (P):** Drivers and driving scenarios (on-road and simulator).
- **Intervention (I): Facial-First** drowsiness detection, a methods that leverage facial cues (face/facial landmarks; eye/eyelid/blink; **PERCLOS**; yawn; head pose; gaze; mouth opening). **Multimodal studies are included** provided a **facial component** is explicitly analyzed and extractable.
- **Comparison (C):** Alternative modalities (e.g., EEG/steering) or state-of-the-art baselines where applicable (not mandatory for bibliometric mapping).
- **Outcomes (O):** Task performance (accuracy/F1/AUROC) and **deployment-oriented metrics** such as **FAR/min**, **TTA**, **latency**, **FPS**, **power/energy** plus **fairness** indicators (e.g., TPR/FPR gaps across day/night, eyewear/mask/hijab, skin tone).
- **Context (C):** Illumination (day/night, RGB/NIR), weather/glare, camera placement, and **edge-device** constraints (e.g., Jetson/RPi+NPU) relevant to ITS/ADAS integration.

From this scope we derive the following **Research Questions (RQs):**

- **RQ1 (Landscape):** What are the publication and citation trends in **facial-feature–based** drowsiness detection (2014–2024)?
- **RQ2 (Actors & Venues):** Which **countries, institutions, authors, and journals** have led the field, and how are they connected through collaboration networks?
- **RQ3 (Themes):** What **predominant and emerging topics** characterize the field based on keyword co-occurrence and thematic evolution?
- **RQ4 (Deployment Readiness):** To what extent do studies report **FAR/min**, **TTA**, **latency**, **FPS**, and **power**, and what are typical values and gaps?
- **RQ5 (Facial-First vs. Multimodal; Fairness):** How prevalent are **multimodal** studies (with an explicit facial stream) relative to **facial-only**, and what evidence exists for **fairness/robustness** across subgroups?

The remainder of the paper is organized as follows. **Section II** details the PRISMA-guided methodology for data collection, screening, and analysis. **Section III** reports bibliometric results (publication trends, geography, institutions, authors, journals, citations). **Section IV** presents thematic analyses and research clusters. **Section V** discusses implications, limitations, and future directions, including explicit **answers to RQ1–RQ5**. **Section VI** concludes with key contributions and recommendations.

2. PRISMA-guided Methodology for Bibliometric Analysis

Scope and Nature of This Study. This work is a **bibliometric analysis**—a quantitative, systematic approach to mapping research landscapes through computational analysis of publication patterns, citation networks, collaboration structures, and thematic evolution. Unlike traditional systematic reviews that include critical appraisal and quality assessment of individual studies, bibliometric analysis focuses on field-level patterns and trends. Our objective is to provide a comprehensive, data-driven overview of the drowsiness detection research domain rather than to evaluate the methodological quality or risk of bias of individual papers. This distinction is important: while quality assessment would be valuable for clinical or applied systematic reviews, it falls outside the scope of bibliometric methodology, which emphasizes quantitative landscape mapping over qualitative evaluation.

2.1. Data Source, Selection Criteria, and Screening Process

Data were obtained from the Scopus database. On January 6th, 2025, a new search was conducted using the following terms: “TITLE-ABS-KEY (drowsiness AND (detection OR recognition OR classification) AND (face OR facial OR eye OR mouth OR ear)) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE , “ar”)) AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (SUBJAREA , “ENGI”) OR LIMIT-TO (SUBJAREA , “COMP”) OR LIMIT-TO (SUBJAREA , “MATH”) OR LIMIT-TO (SUBJAREA , “DECI”))”. This query targets documents published from 2014 to 2024, restricted to English-language journal articles in the subject areas of Engineering, Computer Science, Mathematics, and Decision Sciences. From this query, we retrieved 347 documents, from 187 sources, authored by 1323 researchers.

Rationale for Scopus-Only Approach. We deliberately chose to use Scopus as our sole data source for several methodological reasons. First, Scopus provides comprehensive coverage of engineering and computer science literature with standardized, high-quality metadata (author affiliations, keywords, abstracts, citation counts) essential for robust bibliometric analysis. Second, focusing on a single database ensures consistency and reproducibility – combining multiple databases (e.g., Scopus, Web of Science, IEEE Xplore, Google Scholar) introduces significant challenges in duplicate detection, metadata standardization, and maintaining analytical consistency. Third, many established bibliometric studies in engineering and computer science successfully employ single-database approaches, demonstrating that Scopus-only analyses provide valid and meaningful insights into research landscapes. Fourth, our focus on peer-reviewed journal articles (excluding conference proceedings) aligns with our goal of analyzing mature, consolidated research with stable citation patterns suitable for long-term impact assessment. We acknowledge that this approach may not capture cutting-edge algorithmic innovations often first presented at premier conferences (e.g., CVPR, ICCV, NeurIPS), but our scope emphasizes comprehensive mapping of established, peer-reviewed research rather than tracking the very latest developments.

The query strategy used specific keywords related to drowsiness detection, drowsiness recognition, and drowsiness classification. We focus on facial components, face, eye, mouth, and ear, as these represent key feature extraction regions in facial-feature-based drowsiness detection systems.

Temporal Considerations and Limitations. Data collection occurred on January 6, 2025, which has implications for the completeness of our dataset. Publications from late 2024 may not yet be fully indexed in Scopus, and recent papers (especially those from the second half of 2024) have had limited time to accumulate citations. Consequently, citation metrics for 2024 should be interpreted with appropriate caution, as they represent a snapshot rather than a mature impact. This temporal bias is inherent in any bibliometric study and does not invalidate our findings, but rather contextualizes them within the time frame of data collection.

Figure 1 presents the PRISMA 2020 flow diagram documenting our selection process. The systematic query yielded 347 records from Scopus. Since our query included comprehensive filters at the database level (document type, language, subject area, temporal range), all retrieved records met our inclusion criteria, resulting in zero exclusions during screening. This transparent documentation ensures reproducibility and aligns with established systematic review reporting standards.

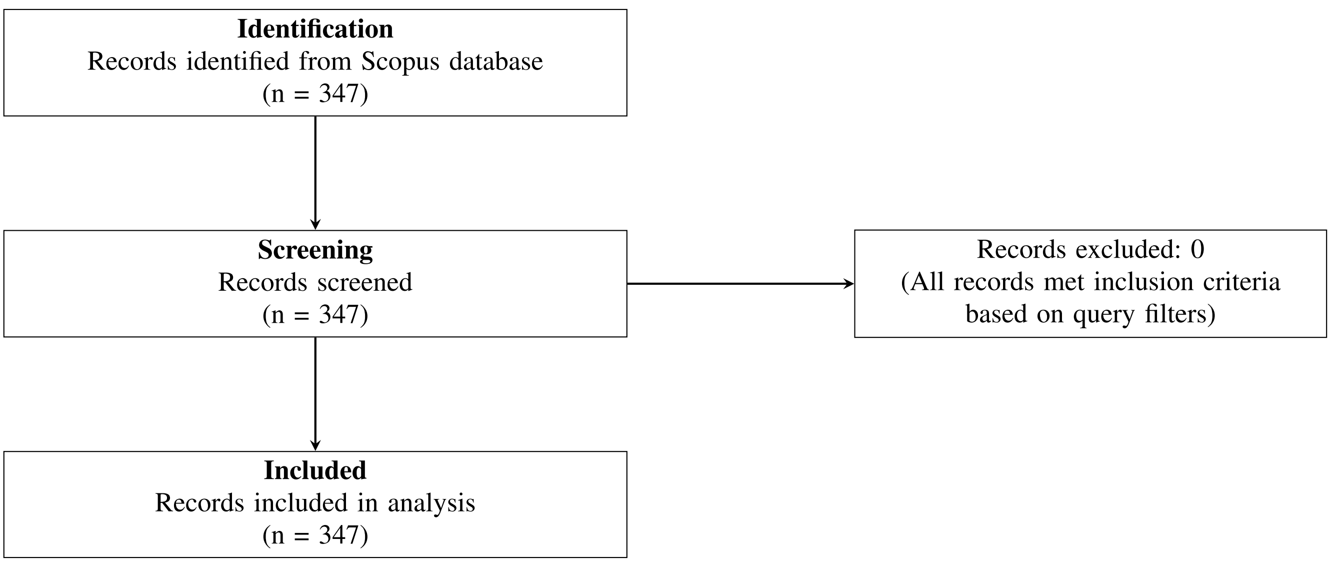

Figure 1. PRISMA 2020 flow diagram showing the systematic selection process for the bibliometric analysis

2.2. Data Processing and Visualization

We utilized RStudio with the bibliometrix package [4.3.2] for bibliometric analysis and VOSviewer to visualize co-occurrence networks and identify emerging research themes. Both VOSviewer and the bibliometrix packages are open source, free and easy to use, providing a clear and concise visualization of key trends in the field.

2.3. Metrics Used

We utilized total citations (TC) to measure a publication's overall impact, while total citations per year (TCpY) indicated sustained influence. The impact factor (IF) was used to assess the prestige of the journal and the fractionality of the article (AF) was calculated to distribute the credit among the co-authors. This study also used single-country publications (SCPs) and multiple-country publications (MCPs) to assess domestic and international research collaboration. All values, including the h-index, are based on Scopus data and may differ from those on other platforms due to variations in indexing.

3. Research Trends and Key Contributions in Drowsiness Detection Using Facial Features in Computer Science

3.1. Trends in Publication Volume and Citation Impact

Analysis of bibliometric data from 2014 to 2024 reveals a consistent annual growth rate of 18.59%. The average citations per document is 18.63, indicating substantial research impact in this domain.

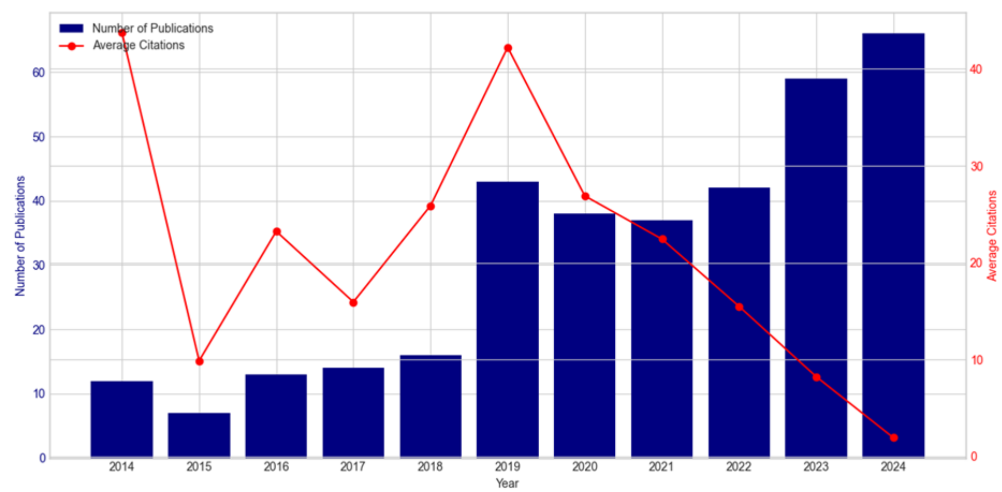

Figure 2. Publication and citation trends of drowsiness detection using facial features

Figure 2 illustrates the average citations per year, enabling identification of two distinct developmental stages. The first stage (2014-2018) is characterized by fewer than 20 papers published annually, representing the field's formative period. The second stage (2019-2024) exhibits significant growth, with 2019 marking the peak of average citations at 42.43 and publications exceeding 40 documents annually.

A notable observation is the declining trend in average citations from 2019 onward, despite continued growth in publication volume. We hypothesize that this pattern may reflect several interrelated factors. First, increased publication volume intensifies citation competition—as more articles enter the field each year, individual papers face greater competition for citation attention. Second, this could indicate field maturation, where research diversifies into specialized niches with smaller citation pools. Third, recency bias affects recent publications (especially from 2023-2024), which have had limited time to accumulate citations. Fourth, the shift toward incremental algorithmic improvements rather than foundational contributions may result in lower per-paper citation rates. However, these interpretations remain hypotheses requiring further longitudinal analysis to confirm. The concurrent increase in publication volume suggests sustained and growing research interest in facial-feature-based drowsiness detection, even as citation dynamics evolve.

It is important to note that the observed trends in publication volume and citation impact are drawn from the Scopus dataset using our specific keyword-based query. Thus, the results may not fully represent the entire landscape of drowsiness detection using facial features research globally in respective years.

3.2. *Analysis of Countries and Regions*

Regarding paper productions, our study reveals a geographic distribution emphasizing both emerging areas for growth and established regional strength. 53 countries contribute to this research domain. Table 1 presents the top ten countries by publication frequency and citation impact. India leads in publication volume with 182 papers, followed by China (100), Saudi Arabia (44), and South Korea (42). In terms of citation impact, China achieves the highest total citations (1370), followed by India (640), Korea (538), and Italy (456). This divergence between publication volume and citation impact highlights varying research influence across nations.

Table 1. Top Contributing Countries related to drowsiness detection using facial features

Country	Freq	Rank	Country	TC	Rank
INDIA	182	1	CHINA	1370	1
CHINA	100	2	INDIA	640	2
SAUDI ARABIA	44	3	KOREA	538	3
SOUTH KOREA	42	4	ITALY	456	4
USA	37	5	SAUDI ARABIA	249	5
PAKISTAN	30	6	USA	237	6
JAPAN	29	7	FRANCE	235	7
MALAYSIA	29	8	IRAN	194	8
IRAQ	22	9	MALAYSIA	186	9
IRAN	19	10	SPAIN	171	10

Concerning Corresponding Author's Countries, analysis of the MCP (Multiple Country Publications) index emphasizes the importance of international research collaboration. Figure 3 shows that China leads in global partnerships with 13 internationally co-authored publications, followed by Saudi Arabia (12), India (6), and Korea (5). Conversely, the SCP (Single Country Publications) index, which reflects domestic research focus, is highest for India (53), followed by China (27), Korea (20), and Japan (9). This pattern reveals that while India demonstrates strong independent research productivity, China and Saudi Arabia excel in fostering international collaborations.

Figure 3 illustrates the distribution of corresponding author's countries in drowsiness detection research, highlighting the MCP index (Multiple Country Publications) and SCP index (Single Country Publications). The MCP index reflects the extent of international collaborations, whereas the SCP index indicates research that is primarily domestic.

Among the top ten countries in terms of international collaboration (MCP), China leads with 13 internationally co-authored publications, followed by Saudi Arabia (12), India (6), Korea (5), USA (4), Italy (4), Pakistan (4), Spain (3), United Kingdom (3), and Malaysia (2). This indicates that these countries are actively engaging in global partnerships, strengthening their research impact.

On the other hand, in terms of domestic research efforts (SCP), India has the highest number of publications (53), demonstrating strong independent research productivity. This is followed by China (27), Korea (20), Japan (9), Malaysia (7), Iran (7), USA (6), Morocco (6), Spain (5), and Australia (4). These numbers indicate that these countries focus more on self-reliant research, with less international collaboration.

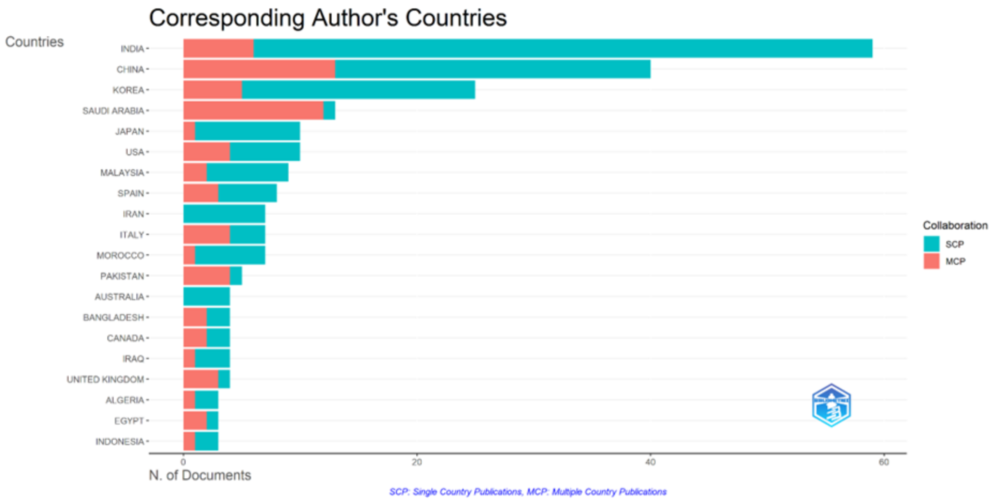

Figure 3. Corresponding authors countries

Overall, the figure highlights the balance between domestic research strength and international collaboration, showing that while some countries (such as China and Saudi Arabia) are leading in global partnerships, others (such as India and Korea) are excelling in independent research productivity.

3.3. Analysis of Affiliations

With respect to institutional contributions, Table 2 demonstrates that publication volume does not necessarily correlate with citation impact. Several institutions exhibit exceptional influence despite moderate publication counts.

Table 2. Top 10 contributing affiliations in drowsiness detection using facial features

Rank	Affiliation	Country	Articles	Total Citations
1	National Institute of Technology	India	8	356
2	Kongu Engineering College	India	6	9
3	Osaka University	Japan	6	32
4	National Institute of Technology Silchar	India	5	64
5	Prince Sattam Bin Abdulaziz University	Saudi Arabia	5	45
6	Shandong University	China	5	240
7	Srm Institute of Science and Technology	India	5	25
8	Department of Computer Science and Engineering, American University of Sharjah	India	4	331
9	Dongguk University	South Korea	4	245
10	King Abdulaziz University	Saudi Arabia	4	48

As shown in Table 2, the National Institute of Technology (India) leads with the highest number of articles (8) and a total of 356 citations, indicating both productivity and research influence. Notably, the Department of Computer Science and Engineering, American University of Sharjah (India), despite having published only 4 articles, has 331 citations, demonstrating exceptional impact per publication.

In terms of global contributions, Dongguk University (South Korea) and Shandong University (China) are also notable, with 4 and 5 publications, respectively, but significantly high citation counts of 245 and 240, showcasing their research importance in the field.

Other affiliations such as Prince Sattam Bin Abdulaziz University (Saudi Arabia) and Osaka University (Japan) also contribute to the field but with varying levels of impact. For instance, Kongu Engineering College (India), despite ranking second in publication count (6 articles), has only 9 total citations, indicating a lower influence relative to its research output.

Overall, the findings highlight that while some institutions excel in producing a high volume of research, others achieve greater visibility and influence through high citation impact, emphasizing the quality and significance of their contributions to the field of drowsiness detection using facial features.

3.4. Analysis of Journals

Regarding publication venues, the 347 documents are distributed across 187 sources, with the top 15 journals contributing 135 papers. We present 15 journals rather than 10 because some high-ranking journals have been discontinued from Scopus. As shown in Table 3, the leading academic journals distinguished by publication volume and impact include: IEEE Access (22 papers, 770 citations), Sensors (22 papers, 385 citations), Multimedia Tools and Applications (14 papers, 324 citations), IEEE Transactions on Intelligent Transportation Systems (11 papers, 678 citations), and Accident Analysis and Prevention (9 papers, 608 citations). These venues represent a mix of computer vision, sensor technology, and transportation safety domains, reflecting the interdisciplinary nature of drowsiness detection research.

Table 3. The top 15 contributing journals related to drowsiness detection using facial features

No	Sources	Articles	TC	JCR	IF	H-Index
1	IEEE ACCESS	22	770	Q1	0.96	242
2	SENSORS	22	385	Q1	0.79	245
3	MULTIMEDIA TOOLS AND APPLICATIONS	14	324	Q1	0.8	106
4	IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS	11	678	Q1	2.58	201
5	ACCIDENT ANALYSIS AND PREVENTION	9	608	Q1	1.9	188
6	INTERNATIONAL JOURNAL OF ADVANCED COMPUTER SCIENCE AND APPLICATIONS	9	91	Q3	0.28	47
7	ELECTRONICS (SWITZERLAND)	8	141	Q2	0.64	83
8	JOURNAL OF ADVANCED RESEARCH IN DYNAMICAL AND CONTROL SYSTEMS	7	5	-	0	31
9	INTERNATIONAL JOURNAL OF INNOVATIVE TECHNOLOGY AND EXPLORING ENGINEERING	6	12	-	0	47
10	INTERNATIONAL JOURNAL OF RECENT TECHNOLOGY AND ENGINEERING	6	17	-	0	31
11	IEEE SENSORS JOURNAL	5	151	Q1	1.08	159
12	APPLIED SCIENCES (SWITZERLAND)	4	190	Q2	0.51	130
13	BULLETIN OF ELECTRICAL ENGINEERING AND INFORMATICS	4	12	Q3	0.28	25
14	IAES INTERNATIONAL JOURNAL OF ARTIFICIAL INTELLIGENCE	4	10	Q3	0.37	22
15	NEURAL COMPUTING AND APPLICATIONS	4	195	Q1	1.26	130

3.5. Analysis of Authors

Concerning author contributions, a total of 1,323 authors have published research on drowsiness detection using facial features. Table 4 presents the top ten contributors based on publication volume. These researchers exhibit diverse specializations: Wang Zhiguo (5 publications, 183 citations) focuses on deep learning architectures; Kim Junhyun (4 publications, 158 citations) specializes in feature-level fusion; Ahmed Manir (3 publications, 141 citations) emphasizes facial subsampling in the eye region; and Dornaika Fadi (3 publications, 99 citations) contributes to temporal analysis techniques.

A total of 1,323 authors have contributed to research on drowsiness detection using facial features. Among them, several key researchers have made significant contributions in specific subfields, demonstrating a diverse range of approaches in this domain.

As shown in Table 4, the most impactful author in terms of citations is Wang Zhiguo from the Center for Psychological Sciences, Zhejiang University, Hangzhou, with five publications and 183 citations, highlighting his contributions to deep learning architectures for drowsiness detection. Similarly, Kim Junhyun from Hanyang University ERICA has four publications and 158 citations, making substantial contributions to feature-level fusion techniques.

Table 4. Top 10 most relevant authors on the basis of publication manner

Author Names	**Affiliation**	**Citations**	**Total Publication**	**Total Citation**
Abubeker KM	Amal Jyothi College Of Engineering (Autonomous)	[15], [16], [17]	3	6
Ahmed Manir	Department Of Electronics And Communication Engineering, National Institute Of Technology Silchar	[18], [19], [20]	3	141
Akrout Belhassen	MIRACL Laboratory, ISIMS PÃ´le Technologique De Sfax, Sfax University	[21], [22], [23], [24]	4	74
Dornaika Fadi	University Of The Basque Country UPV/EHU	[25], [26], [27]	3	99
Kim Junhyun	Hanyang University ERICA	[28], [29], [30], [31]	4	158
Kim Yong-Guk	Department Of Computer Engineering, Sejong University	[32], [33], [34]	3	55
Mahdi Walid	Higher Institute Of Computer Science And Multimedia, University Of Sfax	[22], [23], [24]	3	67
Nozawa Akio	Aoyama Gakuin University	[35], [36], [37], [38]	4	47
Oiwa Kosuke	Aoyama Gakuin University	[35], [36], [37], [38]	4	47
Wang Zhiguo	Center For Psychological Sciences, Zhejiang University, Hangzhou	[39], [40], [41], [42], [43]	5	183
Grand Total			**36**	**877**

In terms of specialized research focus, Abubeker KM from Amal Jyothi College of Engineering (Autonomous) has three publications, emphasizing Internet of Things (IoT) applications in drowsiness detection. Ahmed Manir from the National Institute of Technology Silchar, with three publications and 141 citations, focuses on facial subsampling, particularly in the eye region, which is a critical aspect in gaze-based drowsiness detection.

Akrout Belhassen and Mahdi Walid, both affiliated with institutions in Sfax, Tunisia, have focused on facial feature extraction and their applications in fatigue detection, with total citations of 74 and 67, respectively. Meanwhile, Dornaika Fadi from the University of the Basque Country UPV/EHU has contributed significantly to temporal analysis techniques, accumulating 99 citations across three publications.

Additional contributions include Kim Yong-Guk from Sejong University, who focuses on head pose estimation, a key factor in assessing driver alertness, with three publications and 55 citations. Furthermore, Nozawa Akio and Oiwa Kosuke, both from Aoyama Gakuin University, Japan, have jointly worked on facial skin temperature analysis, each with four publications and 47 citations, demonstrating a unique physiological approach to drowsiness detection.

Overall, the total citation count of 877 across 36 publications by the top ten contributing authors underscores the growing impact of interdisciplinary approaches in drowsiness detection research. These findings reflect the importance of combining various techniques such as deep learning, feature extraction, physiological monitoring, and temporal analysis to develop more robust and accurate drowsiness detection systems.

3.6. Analysis of Significant Manuscripts

Regarding the most globally cited documents, Table 5 reveals key trends in drowsiness detection using facial features. Analysis of the top 10 papers shows methodological evolution from traditional machine learning to deep learning approaches. Early foundational work by Jo et al. (2014) introduced eye state classification using SVM with shorter processing time. Subsequent developments include Deng and Wu's (2019) CNN-based face tracking for low-light environments, Chirra et al.'s (2019) stacked deep CNN with Viola-Jones face detection, and Maior et al.'s (2020) real-time system with personalized adaptation. Recent high-impact contributions such as Dua et al. (2021) demonstrate ensemble deep learning approaches combining multiple architectures (AlexNet, VGG-FaceNet, FlowImageNet, ResNet) for comprehensive feature extraction across diverse conditions.

Table 5. Top 10 most globally cited documents in drowsiness detection using facial features

No	Paper	DOI	TC	TC per Year	Normalized TC
1	JACOBÃ‰ DE NAUROIS C, 2019, ACCID ANAL PREV	10.1016/j.aap.2017.11.038	210	30.00	4.97
2	DENG W, 2019, IEEE ACCESS	10.1109/ACCESS.2019.2936663	170	24.29	4.03
3	JO J, 2014, EXPERT SYS APPL	10.1016/j.eswa.2013.07.108	149	12.42	3.41
4	DUA M, 2021, IEEE TRANS INSTRUM MEAS	10.1109/TIM.2021.3055306	131	26.20	2.82
5	SAVAS BK, 2020, NEURAL COMPUT APPL	10.1007/s00521-020-04815-7	131	21.83	2.98
6	MAIOR CBS, 2020, EXPERT SYST APPL	10.1016/j.eswa.2020.113267	126	21.00	2.87
7	SUN W, 2014, IEEE TRANS VEH TECHNOL	10.1109/TVT.2014.2351774	126	10.50	2.88
8	BISWAL AK, 2021, MULTIMEDIA TOOLS APPL	10.1007/s11042-021-10769-4	98	19.60	2.11
9	REDDY CHIRRA V, 2019, IEEE ACCESS	10.1109/ACCESS.2019.2946814	97	13.86	2.30
10	LIU W, 2019, IEEE TRANS INTELL TRANSP SYST	10.1109/TITS.2018.2885266	94	13.43	2.23

3.7. Deployment Metrics Analysis (RQ4)

To address RQ4 regarding deployment readiness, we conducted a systematic analysis of the top 30 most-cited papers (citation range: 45-315) to assess the extent to which deployment-oriented metrics are reported. We examined each paper's abstract, keywords, and available full-text content for explicit mention of: (1) frames per second (FPS), (2) latency or processing time, (3) time-to-alarm (TTA), (4) false alarm rate (FAR), (5) power or energy consumption, (6) hardware platforms used, and (7) real-time capability claims.

Table 6 presents our findings. The analysis reveals a critical gap in deployment-oriented reporting. Only 1 out of 30 papers (3.3%) explicitly reports FPS values, and none (0%) report latency, TTA, or comprehensive power consumption metrics. While 7 papers (23.3%) claim "real-time" capability, these assertions are rarely substantiated with quantitative performance metrics. Hardware platforms are mentioned in only 3 papers (10.0%), typically referring to Raspberry Pi or embedded GPU systems.

Table 6. Deployment Metrics Reporting in Top 30 Most-Cited Papers

Deployment Metric	Papers Reporting	Percentage
Frames Per Second (FPS)	1/30	3.3%
Latency / Processing Time	0/30	0.0%
Time-to-Alarm (TTA)	0/30	0.0%
False Alarm Rate (FAR)	1/30	3.3%
Power / Energy Consumption	2/30	6.7%
Hardware Platform Specified	3/30	10.0%
Real-Time Capability Claimed	7/30	23.3%

This analysis exposes a significant disconnect between research objectives and deployment considerations. Despite the field's stated focus on real-world driver monitoring systems, the vast majority of highly cited papers do not provide sufficient information to assess practical feasibility. The absence of latency and TTA metrics is particularly concerning, as these are critical for safety-critical applications where delayed warnings could render the system ineffective. Similarly, power consumption reporting is essential for battery-operated edge devices but is largely absent from the literature.

This gap suggests several implications. First, many papers prioritize algorithmic novelty and accuracy metrics over deployment readiness. Second, the lack of standardized benchmarking protocols for deployment metrics hinders comparability across studies. Third, this may indicate that much of the research remains in proof-of-concept stages rather than advancing toward production-ready systems. Addressing this gap requires the community to adopt more comprehensive evaluation frameworks that include deployment-oriented metrics alongside traditional accuracy measures.

3.8. Multimodal vs. Facial-Only Analysis (RQ5)

To address RQ5 regarding the prevalence of multimodal approaches and fairness considerations, we conducted a stratified sampling analysis of 50 papers: 25 from the early period (2014-2018) and 25 from the recent period (2019-2024). We categorized each paper as either "facial-only" (using exclusively facial features such as eyes, mouth, face landmarks) or "multimodal" (combining facial features with physiological signals like EEG/ECG/PPG, thermal imaging, or vehicular dynamics).

Table 7 presents our findings. Among the 50 sampled papers, 37 (74.0%) employ facial-only approaches, while 13 (26.0%) incorporate multimodal signals. Temporal analysis reveals no significant trend toward increased multimodal adoption: early period shows 28.0% multimodal approaches compared to 24.0% in the recent period, suggesting relatively stable preferences over time.

Table 7. Multimodal vs. Facial-Only Approaches (Stratified Sample, N=50)

Category	**Early (2014-2018)**	**Recent (2019-2024)**	**Total**
Facial-Only	18 (72.0%)	19 (76.0%)	37 (74.0%)
Multimodal	7 (28.0%)	6 (24.0%)	13 (26.0%)
Total	25 (100%)	25 (100%)	50 (100%)

Among multimodal approaches, Table 8 shows the distribution of signal types. EEG dominates at 16.0%, followed by thermal imaging (8.0%) and vehicular dynamics (8.0%). ECG, PPG, and other physiological signals remain relatively rare (2.0% each). This distribution reflects ongoing interest in brain activity monitoring for drowsiness detection, though the invasiveness and cost of EEG may limit its practical deployment.

Table 8. Multimodal Signal Type Distribution (N=50)

Signal Type	**Papers**	**Percentage**
EEG (Electroencephalogram)	8/50	16.0%
Thermal Imaging	4/50	8.0%
Vehicular Dynamics	4/50	8.0%
ECG (Electrocardiogram)	1/50	2.0%
PPG (Photoplethysmography)	1/50	2.0%
Other Physiological	1/50	2.0%

Fairness and Bias Considerations. Our analysis also examined explicit discussion of algorithmic fairness, demographic bias, and robustness across subpopulations. Among the 50 sampled papers, only 2 papers (4.0%) explicitly address fairness concerns such as performance variation across skin tones, ethnicities, lighting conditions, or the presence of eyewear/facial coverings. This represents a significant research gap, as facial detection and analysis algorithms are known to exhibit differential performance across demographic groups. The lack of fairness evaluation in drowsiness detection research is concerning given the safety-critical nature of these systems and their potential deployment in diverse real-world populations.

These findings suggest several implications. First, the dominance of facial-only approaches (74%) indicates that researchers prioritize the non-intrusiveness and cost-effectiveness of camera-based systems over potentially more robust multimodal alternatives. Second, the absence of a temporal trend toward multimodal adoption suggests that practical deployment considerations may favor simpler facial-only systems despite their limitations. Third, the critical lack of fairness evaluation highlights an urgent need for the research community to adopt more inclusive evaluation frameworks that assess performance across diverse demographic groups and environmental conditions.

4. Interpreting Findings and Implications in Drowsiness Detection Using Facial Features in Computer Science Research

4.1. Research Overview

A bibliometric analysis of 347 relevant studies from the Scopus database covering drowsiness detection using facial features from 2014 to 2024 reveals significant trends and growth. Throughout this 11-year period, the field achieved an average annual growth rate of 18.59%, with steady growth in publications beginning in 2019. Despite the recency of many publications, average citations per paper have declined in recent years. As discussed in Section 3.1, we hypothesize this may reflect increased citation competition, field maturation, recency bias, or shifts toward incremental improvements rather than foundational contributions.

An analysis of the top ten most globally cited publications reveals that drowsiness detection research commonly employs physiological and behavioural indicators as fused features, utilizing face tracking and eye detection with blink patterns through deep learning architectures (convolutional neural networks) and traditional machine learning (support vector machines). Moreover, hardware and IOT developments are major foci for achieving real-time drowsiness detection.

Geographically, India published 182 papers, followed by China (100), Saudi Arabia (44), South Korea (42), United States of America (37), Pakistan (30), Japan (29), Malaysia (29), Iraq (22), Iran (19). This finding is noteworthy, as most publishing countries are in Asia, suggesting that Asian nations face significant road safety challenges related to driver drowsiness and are actively working to improve detection systems.

Regarding citations, China leads with 1370 citations, followed by India (640), Korea (538), Italy (456), Saudi Arabia (249), United States of America (237), France (235), Iran (194), Malaysia (186), Spain (171). This result shows that the research is impactful in advancing drowsiness detection systems. Moreover, concerning global partnerships for research, China (13), Saudi Arabia (12), India (6), Korea (5), USA (4), Italy (4), Pakistan (4), Spain (3), United Kingdom (3), Malaysia (2) actively collaborate with other countries to accelerate their research for drowsiness detection.

The key institutions driving drowsiness detection using facial features, including National Institute of Technology (India), Kongu Engineering College (India), Osaka University (Japan), National Institute of Technology Silchar (India), Prince Sattam Bin Abdulaziz University (Saudi Arabia), Shandong University (China), Srm Institute of Science and Technology (India), Department of Computer Science and Engineering - American University of Sharjah (India), Dongguk University (South Korea), and King Abdulaziz University (Saudi Arabia) have published numerous papers for drowsiness detection.

Prominent authors, such as Wang Zhiguo (from Center For Psychological Sciences, Zhejiang University, Hangzhou) with five articles and 183 citations underscore his research influence in drowsiness detection.

In terms of journals, high-impact publications such as IEEE ACCESS have played a pivotal role in the dissemination of research. These journals are ranked in the Q1 tier of the JCR and have significantly shaped the field, particularly in drowsiness detection using facial attributes.

This bibliometric analysis is based on a focused Scopus keyword search, which ensures relevance to the study's objectives but may not encompass the full breadth of drowsiness detection using facial features, particularly those employing alternative terminologies or methodologies.

This analysis emphasizes the global and interdisciplinary nature of drowsiness detection using facial features. Most drowsiness detection topics revolve around driver status, encompassing facial expression recognition and real-time drowsiness detection systems, underscoring the importance of integrating emotion detection for enhanced driver safety.

4.2. Exploring the Impact of Drowsiness Detection Using Facial Features in Computer Science Research

In this analysis, both a keyword co-occurrence cluster map (figure 4) and the thematic map (figure 6) were generated to explore the research trends in drowsiness detection using facial features. While the thematic map categorizes research into four quadrants, the clusters from keyword co-occurrence analysis do not align perfectly with these quadrants. Instead, overlaps and intersections reveal the intricate and interconnected nature of the field.

For example, elements from cluster 3, such as eye-tracking are closely aligned with basic themes. Then, cluster 3 such as infrared device also closely aligned with niched themes.

4.2.1. Research Clusters: Thematic Analysis of Keyword Co-Occurrence Figure 4 presents the keyword co-occurrence network analysis, revealing four distinct research clusters that characterize the drowsiness detection domain. Table 9 provides an overview of these clusters, their key focus areas, dominant methodologies, and representative keywords.

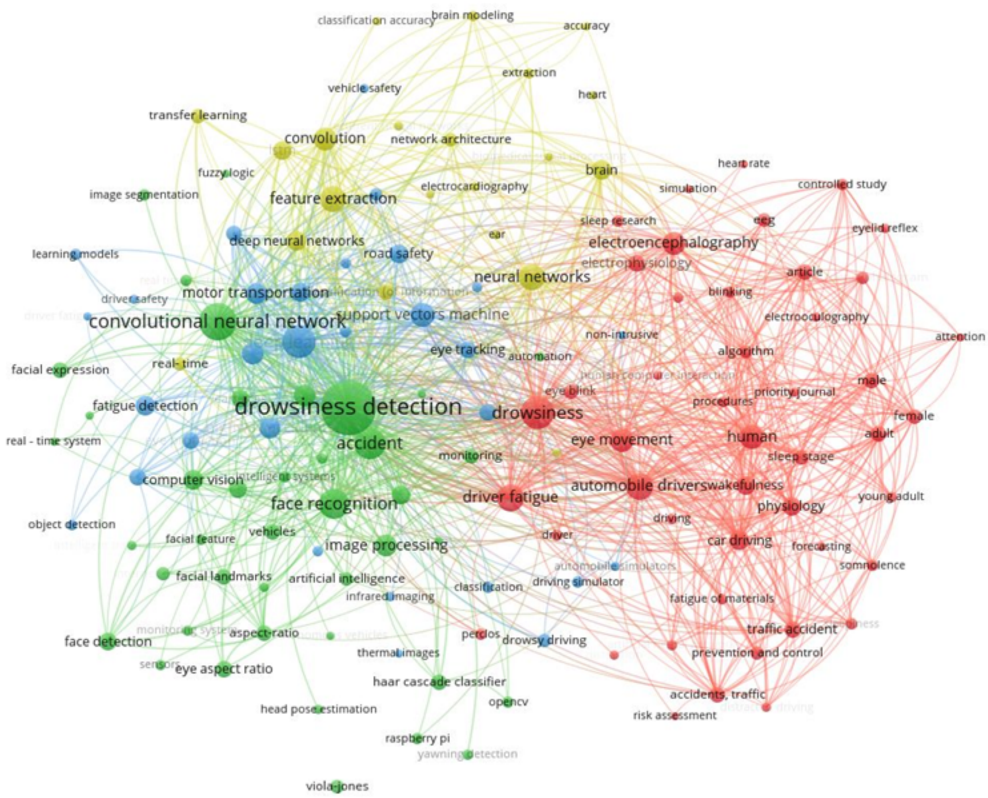

Figure 4. Visualization of cluster maps for keywords grouping

Cluster 1 (Red): Physiological Insights via Neural Networks This research domain focuses on leveraging physiological signals, particularly electroencephalography (EEG), ocular movement parameters, and cardiovascular metrics, to develop advanced drowsiness detection frameworks. The methodological foundation rests on computational models that extract meaningful patterns from complex physiological data streams. Research in this cluster prioritizes the development of interpretable neural network models that effectively bridge the gap between internal physiological processes and externalized behavioral manifestations. This work carries significant implications for advancing understanding of attentional mechanisms and cognitive load assessment through quantifiable physiological markers.

Cluster 2 (Green): Computer Vision-Based Drowsiness Detection This domain centers on implementing computer vision algorithms for real-time driver drowsiness detection to mitigate accident risk. The methodological approach emphasizes extraction and analysis of facial feature parameters, particularly eye aspect ratio calculations, yawning frequency detection, and head position estimation using convolutional neural networks (CNNs) and established computer vision techniques. Research in this cluster prioritizes deployment-focused solutions, with

Table 9. Summary of Four Research Clusters in Drowsiness Detection Using Facial Features

Cluster	Primary Focus	Methodology Emphasis	Key Keywords
Cluster 1 (Red): Physiological Insights via Neural Networks	Physiological signals and deep learning	EEG, ECG analysis using neural networks	EEG, electroencephalogram, brain activity, neural networks, physiological signals
Cluster 2 (Green): Computer Vision-Based Detection	Facial feature extraction and real-time detection	CNNs, image processing, facial landmarks	Drowsiness detection, CNN, face detection, eye aspect ratio, facial landmarks, real-time system
Cluster 3 (Blue): Multi-Modal Fatigue Detection	Accident prevention through sensor fusion	Multi-modal integration, vehicular dynamics	Driver fatigue, accident prevention, sensors, thermal imaging, vehicular dynamics
Cluster 4 (Yellow): Deep Learning for Biomedical Signals	Advanced architectures for signal analysis	Transfer learning, ensemble methods	Deep learning, transfer learning, feature extraction, classification

emphasis on optimization for resource-constrained computational environments such as Raspberry Pi and other embedded systems suitable for in-vehicle implementation. The predominant focus on facial-only approaches reflects the non-invasive nature and cost-effectiveness of camera-based monitoring systems.

Cluster 3 (Blue): Multi-Modal Fatigue Detection for Accident Prevention This research area advances safety systems through multi-modal approaches to driver fatigue detection, integrating oculomotor tracking, thermal imaging techniques, and machine learning classification frameworks. The methodological foundation rests on comprehensive sensor fusion strategies that combine disparate data streams to develop robust predictive models using deep learning architectures, support vector machines (SVMs), and decision tree algorithms. Research protocols typically involve controlled driving simulator environments to establish ground truth measurements while investigating the temporal dynamics of fatigue manifestation across multiple physiological and behavioral indicators. This cluster demonstrates the value of combining facial analysis with complementary modalities for enhanced detection reliability.

Cluster 4 (Yellow): Deep Learning for Biomedical Signal Analysis This domain represents the intersection of deep learning methodology and biomedical signal processing for drowsiness detection applications. The focus encompasses advanced neural network architectures including transfer learning approaches, ensemble methods, and sophisticated feature extraction techniques. Research in this cluster emphasizes algorithmic innovation, exploring novel deep learning paradigms that can effectively process and interpret complex biomedical signals. The methodological sophistication in this cluster reflects the field's maturation, with increasing emphasis on model interpretability, robustness across diverse conditions, and generalization capability beyond training distributions.

These four clusters collectively represent the multifaceted nature of drowsiness detection research. Cluster 2 (Computer Vision) dominates the field, reflecting the practical emphasis on non-invasive, cost-effective solutions. Clusters 1 and 4 represent more sophisticated approaches leveraging physiological signals and advanced deep learning, though these may face deployment challenges due to sensor requirements and computational demands. Cluster 3 bridges these approaches through multi-modal integration, suggesting a future direction that combines the practicality of facial analysis with the robustness of physiological monitoring.

4.3. Keywords and Thematic Analysis

Utilizing the most frequent words, comprehensive keyword analysis provides valuable insights into the dominant themes and trends that shape the field of drowsiness detection using facial features. The 40 most frequently used keywords were identified in Table 10 with prominent terms including “drowsiness detection”, “convolutional neural network”, “drowsiness”, “deep learning”, “driver fatigue”, “machine learning”, “image processing”, “driver monitoring”, “face detection”, and “support vector machine”. This highlights the central focus on driver drowsiness detection using convolutional neural networks. It is worth noting that we applied synonyms to consolidate keywords with identical meanings, such as merging “cnn” and “convolution network” into “convolutional neural network”.

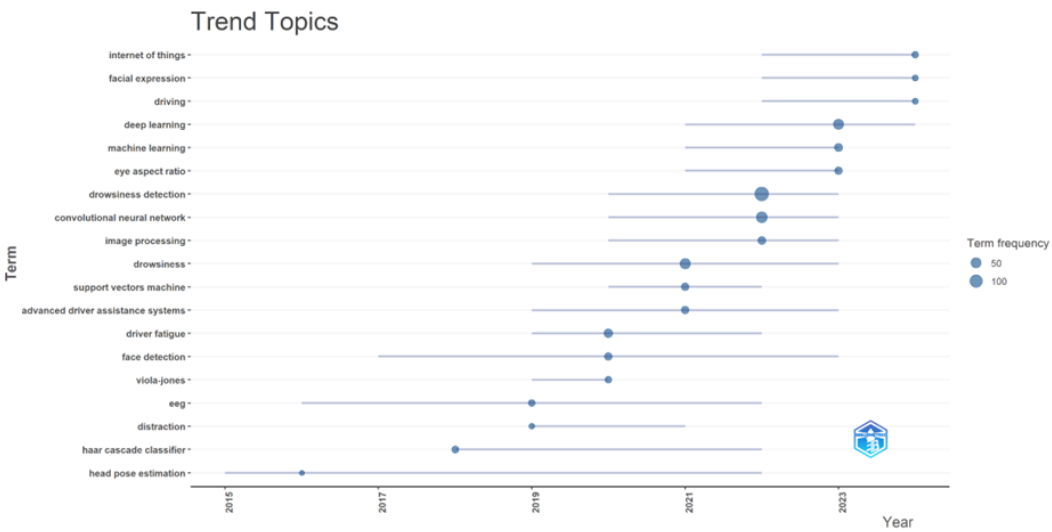

Figure 5. Keyword evolution

Regarding thematic research, we utilized the thematic map from bibliometrix. Figure 6 illustrates four quadrants that describe the maturity and centrality of research themes in the field of drowsiness detection using facial features. In the basic themes quadrant, foundational topics such as drowsiness detection, convolutional neural network, deep learning, eye tracking, eye aspect ratio, machine learning, and mouth aspect ratio are situated, reflecting their well-established relevance in the field. The motor themes quadrant contains driver fatigue detection, driver distraction, driver inattention monitoring, cloud computing, and internet of vehicles, which serve as critical drivers for drowsiness detection advancement. In the niche themes quadrant, specialized topics such as accelerometer, android, eye blink sensors, steering angle, vehicle safety, behavioural measurement, prediction, driving performance and activity, PPG, and 3D head pose estimation suggest potential areas for future research growth in real-time detection. In the emerging/declining themes quadrant, we observe blink detection, eye tracking system, and pupil detection. The possible reason for their declining prominence is the need for individualized calibration, which is not feasible for mass-production drowsiness detection systems.

4.4. Broader Scope

Beyond prominent themes identified through keyword co-occurrence, analysis of trending topics (figure 5) reveals the growing influence of facial expressions, internet of things, driver safety and convolutional neural networks. These findings suggest that facial expressions are important in detecting drowsiness for safety on the road by utilizing convolutional neural networks with real-time response.

Table 10. Top 40 most frequent keywords

No	Words	Occurrences
1	drowsiness detection	135
2	convolutional neural network	65
3	drowsiness	57
4	deep learning	53
5	driver fatigue	28
6	machine learning	24
7	image processing	21
8	driver monitoring	18
9	face detection	18
10	support vectors machine	18
11	advanced driver assistance systems	17
12	eye aspect ratio	17
13	computer vision	15
14	eye detection	15
15	fatigue detection	15
16	road safety	13
17	transfer learning	13
18	facial landmarks	12
19	haar cascade classifier	12
20	eeg	11
21	lstm	11
22	viola-jones	11
23	eye tracking	10
24	internet of things	10
25	opencv	9
26	perclos	8
27	raspberry pi	8
28	artificial intelligence	7
29	classification	7
30	driving	7
31	driving simulator	7
32	electroencephalogram	7
33	eye blink	7
34	image classification	7
35	yawn detection	7
36	cloud computing	6
37	driver behavior	6
38	embedded systems	6
39	feature extraction	6
40	neural networks	6

4.5. Ethical, Societal, and Environmental Considerations

This bibliometric analysis reveals a dynamic and rapidly evolving field of drowsiness detection using facial features, yet several critical ethical and fairness considerations remain significantly underexplored in the literature. Our systematic analysis (Section 3.8) found that only 4% of sampled papers explicitly address algorithmic fairness, demographic bias, or robustness across diverse populations. This gap is particularly concerning given

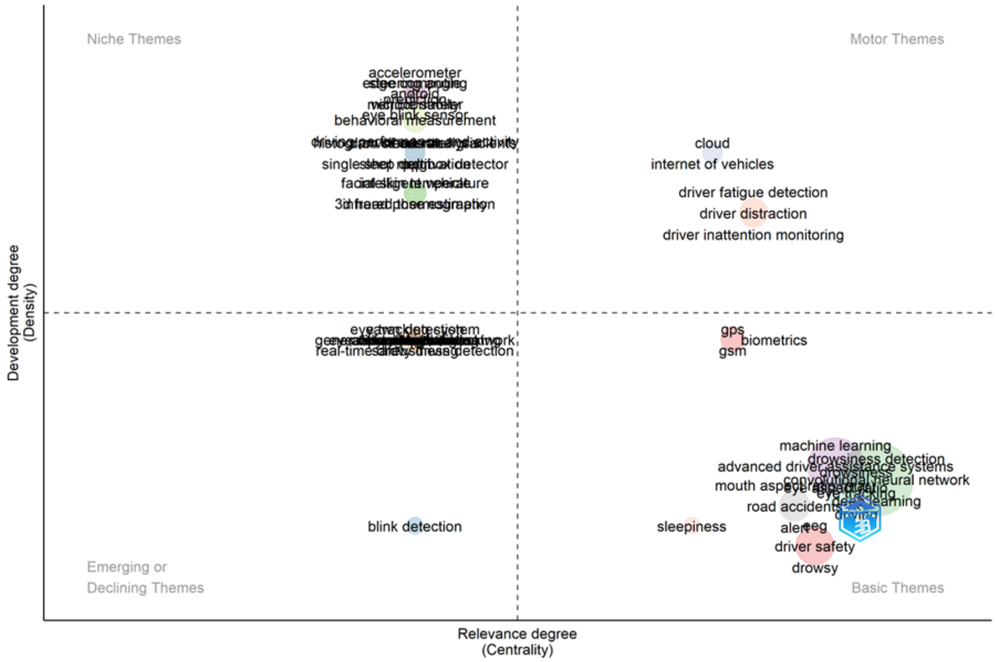

Figure 6. Thematic map of drowsiness detection using facial features

the safety-critical nature of drowsiness detection systems and their potential deployment across diverse real-world populations.

Algorithmic Bias and Fairness Across Demographics. Facial detection and analysis algorithms are well-documented to exhibit differential performance across demographic groups, particularly concerning skin tone, ethnicity, age, and gender. Certain ethnicities with darker skin tones face greater detection challenges, especially in low-light conditions common during night driving—precisely when drowsiness detection is most critical. Research has demonstrated that commercial facial recognition systems can show error rate disparities of up to 34% between demographic groups. In the context of drowsiness detection, such biases could result in systematic under-detection or over-detection for specific populations, creating unequal safety outcomes. For example, systems trained predominantly on lighter-skinned individuals may fail to accurately detect eyelid closure or yawning in darker-skinned drivers, potentially compromising their safety. Similarly, variations in facial morphology across ethnicities (e.g., epicanthic folds affecting eye aspect ratio calculations) can lead to biased performance if datasets lack demographic diversity.

Dataset Representativeness and Training Bias. The lack of diverse, representative datasets compounds these fairness concerns. Many drowsiness detection datasets are collected in controlled laboratory settings with limited demographic diversity, potentially introducing systematic biases that persist when models are deployed in real-world conditions. Our analysis reveals minimal discussion in the literature regarding dataset composition, demographic representation, or validation across diverse populations. This represents a critical gap, as models trained on non-representative data may exhibit reduced performance or systematic errors for underrepresented groups. The field requires standardized protocols for dataset collection that ensure demographic diversity, environmental variation (day/night, urban/rural), and representation of edge cases (eyewear, facial coverings, facial hair, aging effects).

Privacy Concerns and Continuous Monitoring. Drowsiness detection systems necessitate continuous facial monitoring, raising substantial privacy concerns. Unlike discrete authentication systems, these applications involve persistent capture and analysis of biometric data throughout driving sessions. This continuous monitoring creates extensive records of facial images, behavioral patterns, and potentially sensitive information about driver health and cognitive state. Regulatory frameworks such as the European Union's General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) impose strict requirements on biometric data collection, storage, and processing. Compliance challenges include obtaining informed consent for continuous monitoring, ensuring data minimization (collecting only necessary data), implementing secure storage with encryption, establishing clear data retention policies, and providing transparency about data usage. Organizations deploying these systems must carefully balance safety objectives with individual privacy rights, implementing robust data governance frameworks that protect sensitive biometric information while enabling effective drowsiness detection.

Illumination and Environmental Robustness. Our analysis identifies illumination variation as a persistent challenge inadequately addressed in current research. Low-light conditions, glare, shadows, and rapid lighting transitions (e.g., tunnel entry/exit) significantly impact facial feature detection accuracy. These environmental variations affect demographic groups differentially—darker skin tones become even more challenging to detect in low-light conditions, exacerbating existing biases. The field requires more robust image enhancement techniques, multi-spectral imaging approaches (combining visible and near-infrared), and explicit evaluation protocols that assess performance across diverse lighting conditions. Some researchers have begun exploring infrared imaging and thermal sensing as complementary modalities less susceptible to visible-light variations, though these approaches introduce additional cost and complexity.

Transparency, Explainability, and Trust. The increasing deployment of deep learning models in drowsiness detection raises concerns about algorithmic transparency and explainability. Safety-critical applications demand interpretable decision-making processes, yet many state-of-the-art deep neural networks operate as "black boxes" with limited interpretability. When a system triggers a drowsiness alert (or fails to trigger one), drivers and transportation authorities need to understand the reasoning behind these decisions. This is particularly important for building user trust, debugging system failures, meeting regulatory requirements, and addressing potential liability issues in accident investigations. The field should prioritize development of interpretable models, attention visualization techniques that highlight which facial features drove specific decisions, and uncertainty quantification methods that communicate model confidence levels.

Recommendations for Future Research. To address these ethical gaps, we recommend: (1) mandatory reporting of dataset demographic composition and fairness evaluations across protected attributes in all publications; (2) development of standardized fairness benchmarks for drowsiness detection that include diverse demographic groups and environmental conditions; (3) adoption of privacy-preserving techniques such as edge processing (on-device inference without transmitting raw images) and federated learning (training models without centralizing sensitive data); (4) explicit evaluation of performance across skin tones using established scales (e.g., Fitzpatrick scale); (5) investigation of fairness-aware training objectives that explicitly penalize demographic performance disparities; (6) collaboration with ethicists, legal scholars, and representatives from diverse demographic communities in system design and evaluation; and (7) development of clear ethical guidelines and best practices specific to drowsiness detection systems. Addressing these ethical considerations is not merely a technical challenge but a moral imperative to ensure that safety technologies benefit all individuals equitably, regardless of demographic characteristics.

5. Limitations and Future Works

While this study provides valuable insights into the development and growth of drowsiness detection using facial features, several limitations should be acknowledged.

Data Source and Scope. First, this analysis relies exclusively on Scopus data, which may overlook relevant innovations published in other databases such as Web of Science or conference proceedings from premier venues (e.g., CVPR, ICCV, NeurIPS). As discussed in Section 2, we deliberately chose Scopus for its comprehensive coverage, standardized metadata, and suitability for bibliometric analysis. We focused on peer-reviewed journal articles to analyze mature, consolidated research with stable citation patterns. While conference proceedings often present cutting-edge algorithmic innovations, journal articles typically provide more complete methodological descriptions, comprehensive evaluations, and extensive references suitable for long-term impact assessment.

Nevertheless, we acknowledge that this scope decision means our analysis may not capture the most recent algorithmic developments presented at conferences, and future bibliometric work could complement our findings by analyzing conference proceedings to identify emerging trends earlier in their lifecycle.

Temporal Coverage and Recency Bias. Second, our analysis spans 2014–2024 (an 11-year period), which we characterize as “a decade” to represent approximately ten years of consolidated research progress. Data collection occurred on January 6, 2025, meaning that publications from late 2024 may not yet be fully indexed in Scopus and have had limited time to accumulate citations. Consequently, citation metrics for 2024 should be interpreted with appropriate caution. This temporal bias is inherent in any bibliometric study but does not invalidate our findings regarding long-term trends and patterns.

Scope of Bibliometric Analysis. Third, as a bibliometric analysis rather than a traditional systematic review, this study focuses on quantitative mapping of research patterns rather than critical appraisal of individual study quality. We do not assess methodological rigor, risk of bias, or reproducibility of individual papers—such quality assessment would be valuable for future systematic reviews but falls outside the scope of bibliometric methodology. Our objective is to provide a comprehensive, data-driven overview of the field’s landscape, identifying trends, gaps, and research clusters through computational analysis of publication patterns, citations, and keyword co-occurrence.

Sampling for Deployment and Multimodal Analysis. Fourth, our systematic analyses for RQ4 (deployment metrics) and RQ5 (multimodal approaches) are based on representative samples rather than the complete dataset. For RQ4, we analyzed the top 30 most-cited papers (citation range: 45-315), which represent highly influential work but may not fully capture practices in lower-impact publications. For RQ5, we employed stratified sampling of 50 papers (25 from 2014-2018, 25 from 2019-2024) to ensure temporal balance. While these sampling strategies are methodologically sound and yield valuable insights, they provide a focused rather than exhaustive view of these specific research questions. The critical gaps we identified—particularly the near-absence of deployment metrics (Section 3.7) and limited fairness evaluation (Section 3.8)—are striking even within these influential samples, suggesting these issues are likely even more prevalent in the broader literature.

Focus on Facial Features. Fifth, we focused exclusively on facial-feature-based approaches rather than other modalities such as electroencephalography (EEG), photoplethysmography (PPG), or electrocardiography (ECG). This decision reflects the practical advantages of facial detection: it is non-intrusive, requires no physical contact or sensor attachment, utilizes readily available and inexpensive hardware (webcams), and benefits from mature computer vision frameworks and libraries. In contrast, physiological signal acquisition requires specialized equipment, skilled personnel for sensor placement, and can be uncomfortable or movement-restrictive for users. Nevertheless, our analysis reveals that 26% of sampled papers do incorporate multimodal approaches (Section 3.8), indicating continued interest in combining facial analysis with complementary signals to improve detection reliability. This multimodal integration represents an important research direction, though practical deployment considerations currently favor facial-only approaches.

Future Research Directions. Based on our comprehensive analysis, we recommend the following high-priority research directions:

1. **Algorithmic Fairness and Robustness:** Develop and validate drowsiness detection systems across diverse demographic groups (skin tones, ethnicities, age ranges, gender) and environmental conditions (day/night, varying illumination, weather conditions). Establish standardized fairness benchmarks using representative datasets and explicit evaluation of performance disparities across protected attributes. Address the compounding challenge of low-light detection for darker skin tones through robust image enhancement, multi-spectral imaging, or infrared sensing.
2. **Deployment-Oriented Evaluation:** Adopt comprehensive evaluation frameworks that include deployment-critical metrics beyond classification accuracy. Future papers should systematically report: frames per second (FPS), latency/processing time, time-to-alarm (TTA), false alarm rate (FAR/min), hardware specifications, power consumption, and computational complexity. Evaluate systems on edge devices (Raspberry Pi, Jetson Nano, mobile processors) to assess real-world feasibility. Currently, only 3.3% of top-cited papers report FPS, and none report latency or TTA (Section 3.7), representing a critical gap.
3. **Privacy-Preserving Architectures:** Develop edge-processing approaches that perform inference locally without transmitting raw facial images to cloud servers, addressing GDPR/CCPA compliance concerns.

Investigate federated learning approaches that enable model improvement across distributed datasets without centralizing sensitive biometric data. Design transparent data governance frameworks that balance safety objectives with individual privacy rights.

4. **Interpretability and Explainability:** Prioritize development of interpretable models that provide transparent decision-making processes. Implement attention visualization techniques to show which facial features drove specific drowsiness alerts. Develop uncertainty quantification methods to communicate model confidence levels, supporting user trust and facilitating debugging.
5. **Personalization and Adaptation:** Explore few-shot learning and online adaptation techniques that allow systems to personalize to individual driver characteristics (baseline blink rates, eye morphology, typical head pose) without requiring extensive per-driver calibration. Investigate meta-learning approaches that enable rapid adaptation to new users while preserving privacy.
6. **Longitudinal Validation:** Conduct naturalistic driving studies that evaluate system performance over extended periods in real-world conditions, moving beyond controlled laboratory settings and driving simulators. Assess system reliability across different times of day, road types, and driving durations. Investigate how performance degrades over time due to environmental factors (camera lens degradation, lighting changes, seasonal variations).
7. **Interdisciplinary Collaboration:** Foster collaboration between computer vision researchers, human factors engineers, psychologists, ethicists, and transportation safety experts. Integrate insights from neuroscience regarding fatigue manifestation, human factors research on attention dynamics, and legal scholarship on liability and privacy. Engage representatives from diverse demographic communities in system design and evaluation to ensure equitable outcomes.

By addressing these limitations and pursuing these research directions, the drowsiness detection community can accelerate translation of academic innovations into practical, equitable, and effective transportation safety technologies that save lives across all demographic groups and environmental conditions.

6. Conclusion

This comprehensive bibliometric analysis of 347 publications spanning 2014–2024 has systematically mapped the evolution, key contributors, and thematic landscape of facial-feature–based drowsiness detection research. The findings reveal a rapidly expanding field with an 18.59% annual growth rate, marked by a decisive shift toward deep learning architectures, IoT integration, and deployment-oriented solutions after 2019.

Geographic analysis identifies Asia—particularly India and China—as the dominant research hub, reflecting both regional transportation safety challenges and computational capacity. International collaboration analysis reveals China and Saudi Arabia leading in multi-country partnerships (13 and 12 international collaborations respectively), while India demonstrates strong domestic research productivity with 53 single-country publications. This pattern highlights the global yet regionally concentrated nature of drowsiness detection research, with significant interdisciplinary contributions from computer science, psychology, human factors engineering, and biomedical signal processing.

Citation impact analysis reveals that while publication volume continues to rise, average citations per paper have declined since 2019. As discussed in Section 3.1, we hypothesize this pattern may reflect increased citation competition as the field expands, field maturation into specialized niches, recency bias for recent publications, or shifts toward incremental algorithmic improvements. However, the concurrent growth in publication volume indicates sustained research interest and continued field vitality.

Through co-occurrence network analysis and thematic mapping, four major research clusters were identified: (1) physiological insights via neural networks, (2) computer vision-based drowsiness detection, (3) multi-modal fatigue detection for accident prevention, and (4) deep learning for biomedical signal analysis. Cluster 2 (computer vision-based approaches) dominates the field, reflecting the practical emphasis on non-invasive, cost-effective camera-based systems. The interdisciplinary nature of these clusters underscores the value of combining expertise from multiple domains to advance drowsiness detection capabilities.

Our systematic analysis surfaces critical research gaps with significant implications for real-world deployment. First, deployment readiness assessment (RQ4, Section 3.7) reveals alarming deficiencies in reporting deployment-critical metrics: only 3.3% of top-cited papers explicitly report frames per second (FPS), and none report latency, time-to-alarm (TTA), or comprehensive power consumption metrics. Despite 23.3% claiming "real-time" capability, these assertions are rarely substantiated with quantitative evidence. This gap severely limits assessment of practical feasibility and hinders translation of research into production-ready systems.

Second, multimodal analysis (RQ5, Section 3.8) demonstrates that 74% of research focuses exclusively on facial features, while 26% incorporate physiological or vehicular signals. Notably, this ratio shows no significant temporal trend (28% multimodal in 2014-2018 vs. 24% in 2019-2024), suggesting stable preferences despite potential robustness advantages of multimodal fusion. Among multimodal approaches, EEG dominates (16%), followed by thermal imaging and vehicular dynamics (8% each).

Third, fairness and bias evaluation (Section 3.8, Section 4.4) remains critically underexplored: only 4% of sampled papers explicitly address algorithmic fairness, demographic bias, or robustness across diverse populations. This is particularly concerning given well-documented performance disparities in facial recognition systems across skin tones and ethnicities, which can be exacerbated in low-light conditions common during night driving. The absence of systematic fairness evaluation represents a serious ethical gap in safety-critical systems that must serve all demographic groups equitably.

Fourth, limited attention to environmental robustness—particularly low-light conditions, illumination variations, and adverse weather—constrains real-world applicability. Systems trained and evaluated primarily in controlled laboratory settings may exhibit degraded performance when deployed in naturalistic driving environments with diverse lighting conditions, camera angles, and driver characteristics.

These gaps represent high-impact opportunities for advancing the field toward practical, equitable, and effective deployment in Advanced Driver Assistance Systems (ADAS) and autonomous vehicles.

Future research priorities must address these multifaceted challenges through: (1) comprehensive evaluation frameworks incorporating deployment metrics, fairness assessments, and environmental robustness testing; (2) privacy-preserving edge architectures that enable real-time inference without centralizing sensitive biometric data; (3) interpretable models with transparent decision-making processes to build user trust and facilitate debugging; (4) personalization strategies that adapt to individual driver characteristics while preserving privacy; (5) longitudinal validation in naturalistic driving environments; and (6) interdisciplinary collaboration bridging computer vision, human factors, psychology, ethics, and transportation safety expertise.

This bibliometric analysis provides the research community with a comprehensive, data-driven foundation for understanding the current state of facial-feature-based drowsiness detection and charting strategic directions for future work. By addressing the identified gaps—particularly deployment readiness, algorithmic fairness, and environmental robustness—researchers can accelerate translation of academic innovations into life-saving transportation safety technologies that benefit all individuals equitably, regardless of demographic characteristics or environmental conditions. The field stands at a critical juncture where attention to these practical, ethical, and technical challenges will determine whether drowsiness detection systems fulfill their promise of reducing fatigue-related accidents and saving lives on a global scale.

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