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Lifestyle-Driven Insomnia: A Comprehensive Review and Predictive Modeling Perspectives for Early Risk Forecasting

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***Abstract*—Sleep is a fundamental physiological process that supports cognitive functioning, emotional stability, and overall physical health. However, the prevalence of insomnia has increased substantially in recent years, largely influenced by evolving lifestyle patterns such as prolonged digital engagement, irregular work schedules, psychological stress, sedentary behavior, and unhealthy dietary habits. This review paper presents a comprehensive examination of the relationship between modern lifestyle factors and the growing incidence of insomnia, with particular emphasis on the potential of data-driven approaches for early detection and risk forecasting. The study synthesizes findings from existing literature covering clinical sleep research, behavioral studies, wearable sensing technologies, and machine learning-based predictive models. A comparative analysis of previous studies is conducted by evaluating commonly used datasets, feature sets, learning algorithms, predictive performance, and reported limitations. The review reveals that while several machine learning techniques—including Support Vector Machines, Random Forest models, and deep learning architectures—have demonstrated promising results in identifying sleep-related abnormalities, many studies rely on limited datasets, single-modality inputs, or short-term observational data. Furthermore, current research often lacks integrated frameworks capable of combining behavioral, physiological, and contextual lifestyle information for reliable insomnia forecasting.**

To address these limitations, the paper proposes a conceptual predictive framework that integrates lifestyle monitoring with machine learning-driven risk assessment. The framework outlines multiple stages including lifestyle data acquisition from wearable devices, smartphone sensors, and self-reported surveys, followed by data preprocessing, feature extraction, and predictive modeling. By analyzing behavioral indicators such as sleep duration patterns, activity levels, stress indicators, and physiological signals, the system aims to classify individuals into different insomnia risk categories including low, moderate, and high risk. The proposed framework highlights the potential of multimodal data integration for improving prediction accuracy and enabling proactive sleep health management. Additionally, the paper discusses key challenges associated with data privacy, dataset availability, and model interpretability, while emphasizing the need for explainable artificial intelligence in healthcare applications. The findings suggest that combining continuous lifestyle monitoring with intelligent analytics can facilitate early identification of insomnia risks and support personalized preventive interventions. The study concludes that future advancements in digital health technologies, wearable sensing, and artificial intelligence can pave the way for scalable and personalized insomnia monitoring systems capable of enhancing preventive healthcare and improving long-term sleep health outcomes.

***Keywords*—Insomnia Prediction, Sleep Disorders, Lifestyle Analytics, Machine Learning in Healthcare, Digital Health Monitoring, Wearable Sleep Sensors, Behavioral Sleep Analysis, Artificial Intelligence for Healthcare, Sleep Quality Assessment, Predictive Health Analytics**

I. INTRODUCTION

Sleep is a fundamental biological process essential for maintaining physiological homeostasis, cognitive performance, and psychological well-being. Adequate and high-quality sleep contributes significantly to memory consolidation, emotional regulation, immune system functioning, and metabolic balance. Modern neuroscientific research has demonstrated that sleep plays a crucial role in synaptic plasticity and neural restoration processes that occur during different sleep stages [1], [2]. Disruption of normal sleep patterns may lead to cognitive impairment, weakened immune responses, metabolic irregularities, and emotional instability. In contemporary societies characterized by rapid urbanization, extended work schedules, and pervasive digital connectivity, sleep disturbances have become increasingly common across diverse demographic groups [3]. Among various sleep disorders, insomnia is considered the most prevalent and impactful condition affecting global populations.

Insomnia is generally defined as persistent difficulty in initiating or maintaining sleep, accompanied by daytime impairment such as fatigue, irritability, or reduced concentration [4]. The importance of sleep for human health extends far beyond basic rest; it is closely associated with cognitive productivity, emotional stability, and long-term physiological resilience. Studies indicate that individuals experiencing chronic sleep deprivation often exhibit reduced attention span, impaired decision-making capabilities, and diminished academic or occupational performance [5]. Furthermore, insufficient sleep has been associated with increased susceptibility to chronic conditions including cardiovascular disease, diabetes, obesity, and neurodegenerative disorders [6]. In addition to physical health risks, poor sleep quality is strongly linked to psychological disorders such as depression and anxiety, creating a bidirectional relationship between mental health and sleep disturbances [7].

Short-term sleep deprivation may lead to temporary cognitive decline and mood instability, whereas long-term insomnia can contribute to persistent health deterioration and reduced life expectancy [8]. In occupational environments, especially those involving shift work or high cognitive demand, inadequate sleep significantly affects productivity and decision-making efficiency. Consequently, sleep health is increasingly recognized as an important determinant of workforce productivity and societal well-being.

The global prevalence of insomnia has increased noticeably over the past two decades. Epidemiological studies suggest that approximately 10–30% of adults worldwide report symptoms of insomnia, while nearly 6–10% meet the clinical diagnostic criteria for chronic insomnia disorder [9], [10]. The prevalence of insomnia varies considerably across geographic regions, socio-economic conditions, and age groups. For example, large-scale surveys in North America and Europe have reported insomnia prevalence rates ranging from 20% to 35%, while studies conducted in Asian countries indicate prevalence rates between 15% and 25% [11], [12].

Age-related differences in insomnia prevalence are also widely documented. Adolescents and young adults frequently experience sleep disturbances due to academic pressure, social media exposure, and irregular sleep schedules [13]. Conversely, older adults often report insomnia symptoms related to physiological aging, chronic illness, and medication usage [14]. Additionally, urban populations tend to exhibit higher insomnia prevalence compared to rural populations, primarily due to environmental noise, occupational stress, and increased digital device usage [15].

The COVID-19 pandemic further intensified global sleep disturbances by altering daily routines, increasing psychological stress, and expanding remote working practices. Several post-pandemic studies reported a substantial rise in insomnia symptoms among healthcare workers, students, and remote employees [16]. Changes in lifestyle behavior, including increased screen exposure, irregular work schedules, and reduced physical activity, have contributed to widespread disruption of circadian rhythms.

Table I summarizes representative statistics of insomnia prevalence across selected countries over the past two decades based on epidemiological studies.

TABLE I: Representative prevalence of insomnia symptoms across countries (2005–2024)

Country	2005	2015	2024 (Approx.)
United States	23%	28%	30%
United Kingdom	21%	26%	29%
China	15%	18%	22%
India	13%	18%	23%
Japan	20%	24%	27%
Australia	22%	27%	31%
Germany	19%	23%	26%
Brazil	18%	22%	25%

Beyond its clinical implications, insomnia has significant socio-economic consequences. Sleep-related productivity losses are estimated to cost billions of dollars annually due to absenteeism, reduced work efficiency, and increased workplace accidents [17]. For instance, economic analyses have suggested that insufficient sleep results in substantial productivity losses in developed economies such as the United States, Japan, and Germany [18]. Additionally, insomnia often leads to increased healthcare utilization, including physician consultations, pharmacological treatments, and mental health interventions. The association between insomnia and mental health disorders is particularly notable, as persistent sleep disturbances can exacerbate depression, anxiety, and stress-related conditions [19]. Consequently, insomnia represents both a public health concern and an economic challenge for healthcare systems worldwide.

The rapid expansion of digital technologies and modern lifestyle behaviors has introduced new dimensions to sleep research. Increased reliance on smartphones, late-night internet usage, sedentary work patterns, and irregular dietary habits have significantly altered daily routines, thereby influencing sleep patterns. At the same time, the emergence of wearable health technologies and mobile health applications has created opportunities to collect continuous behavioral and physiological data related to sleep. These technological advancements enable researchers to explore predictive analytics for sleep disorders using large-scale digital health datasets [20].

In recent years, machine learning and data-driven approaches have shown promising potential for forecasting sleep disturbances by analyzing behavioral patterns, physiological signals, and environmental variables. Predictive models based on wearable sensors, smartphone activity logs, and lifestyle indicators may enable early identification of individuals at risk of insomnia. Such predictive systems could support preventive healthcare strategies and personalized sleep management solutions.

Motivated by these developments, this review aims to provide a comprehensive examination of insomnia from both clinical and technological perspectives. Specifically, the objectives of this review are fivefold: (1) to analyze major lifestyle determinants that influence sleep quality and insomnia risk; (2) to examine traditional clinical and questionnaire-based approaches used for insomnia detection; (3) to evaluate recent machine learning techniques applied to sleep disorder prediction; (4) to identify key research gaps in lifestyle-based insomnia forecasting; and (5) to propose a conceptual predictive framework that integrates behavioral data and machine learning techniques for early insomnia risk assessment.

To conceptually illustrate the multidimensional nature of insomnia risk, Fig. 1 presents a simplified framework highlighting the interaction between lifestyle factors, physiological mechanisms, and predictive analytics for insomnia forecasting.

The remainder of this paper is organized as follows. Section II provides a clinical background of insomnia and its physiological mechanisms. Section III reviews lifestyle factors that influence sleep quality. Section IV discusses traditional diagnostic methods for insomnia detection. Section V examines machine learning approaches for predicting sleep disturbances. Section VI presents a comparative analysis of existing studies, while Section VII identifies key research gaps. Finally, Section VIII outlines a conceptual predictive framework for lifestyle-based insomnia forecasting and Section IX concludes the paper with future research directions.

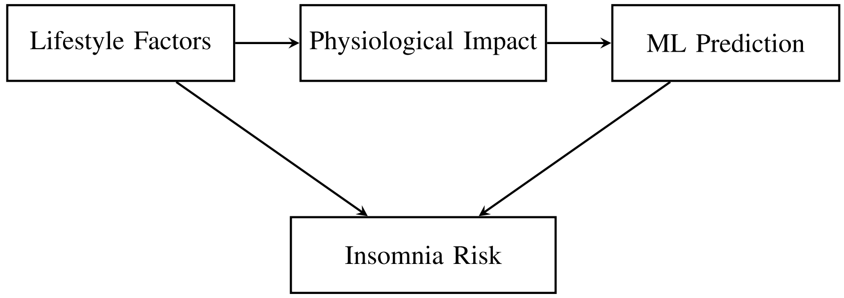

Fig. 1: Conceptual relationship between lifestyle factors, physiological responses, and predictive modeling for insomnia risk.

II. Background of Insomnia

Sleep disorders have received increasing attention in clinical medicine and public health research due to their growing prevalence and substantial impact on human well-being. Among these disorders, insomnia represents the most frequently reported sleep disturbance across diverse populations. Insomnia is not merely a temporary inconvenience but a complex neurophysiological condition influenced by behavioral, environmental, and biological factors. Understanding its clinical definition, classification, underlying mechanisms, and associated health consequences is essential for developing effective diagnostic and predictive systems.

A. *Definition and Clinical Overview*

Insomnia is clinically defined as a persistent difficulty in initiating sleep, maintaining sleep, or experiencing restorative sleep despite adequate opportunity for rest. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), insomnia disorder is characterized by dissatisfaction with sleep quantity or quality accompanied by significant daytime impairment [21]. The *International Classification of Sleep Disorders* (ICSD-3) similarly describes insomnia as a condition involving recurrent sleep disturbances associated with fatigue, cognitive dysfunction, and reduced daytime functioning [22]. These standardized diagnostic frameworks provide clinicians with structured criteria to differentiate insomnia from other sleep-related disorders.

Clinical evaluation of insomnia typically considers several key parameters. These include difficulty falling asleep within a reasonable time frame, frequent awakenings during the night, and early morning awakening with an inability to return to sleep. These symptoms must persist for a minimum duration—typically several nights per week for at least three months—to meet the criteria for chronic insomnia disorder [23]. The clinical assessment also involves evaluating daytime consequences such as fatigue, mood disturbances, and impaired concentration. Epidemiological studies indicate that the prevalence of clinically significant insomnia symptoms has gradually increased across multiple regions during the past two decades, reflecting the growing influence of modern lifestyle behaviors and psychosocial stressors [24].

B. *Types of Insomnia*

Insomnia can be categorized into several clinical types depending on duration, underlying causes, and associated conditions. Figure 2 illustrates a conceptual taxonomy of insomnia classifications widely discussed in sleep medicine literature.

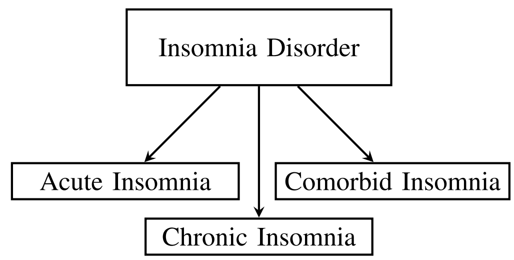

Fig. 2: Clinical taxonomy of insomnia based on duration and associated conditions.

Acute insomnia is generally short-term and often arises in response to temporary stressors such as life transitions, illness, or emotional distress. Episodes of acute insomnia may last from a few days to several weeks and typically resolve once the triggering factors diminish [25].

Chronic insomnia, by contrast, persists for longer durations and may extend for several months or years. According to clinical guidelines, chronic insomnia is diagnosed when sleep disturbances occur at least three times per week for a period exceeding three months [26]. Individuals experiencing chronic insomnia frequently report sustained fatigue, reduced cognitive performance, and emotional instability.

A third category, comorbid insomnia, refers to sleep disturbances that occur in association with other medical or psychiatric conditions. Examples include insomnia linked to chronic pain disorders, cardiovascular disease, anxiety disorders, and depression [27]. In such cases, insomnia may both influence and be influenced by the underlying health condition, creating a complex bidirectional relationship.

C. *Symptoms of Insomnia*

The symptoms of insomnia manifest in both nocturnal sleep patterns and daytime functioning. While difficulty initiating sleep is one of the most commonly reported symptoms, individuals may also experience fragmented sleep characterized by frequent nighttime awakenings. Early morning awakening, during which individuals wake significantly earlier than desired and cannot return to sleep, is another characteristic symptom [28].

Daytime consequences are equally significant. Individuals with persistent insomnia often experience fatigue, irritability, mood instability, and difficulty concentrating. Cognitive impairments such as reduced attention span and slower reaction times may also occur. These symptoms can negatively influence professional productivity, academic performance, and interpersonal relationships [29].

The symptom progression of insomnia can be conceptualized as a sequence of interacting physiological and behavioral effects. Figure 3 presents a simplified flowchart illustrating the relationship between sleep disruption and daytime impairment.

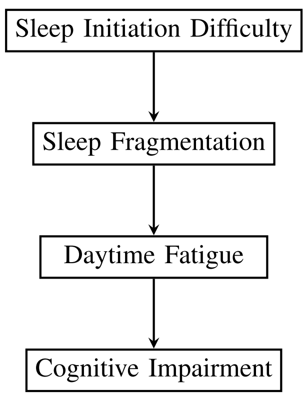

Fig. 3: Flowchart illustrating progression from sleep disturbance to daytime impairment.

D. Physiological and Neurological Mechanisms

The underlying mechanisms of insomnia involve complex interactions between circadian rhythms, neuroendocrine regulation, and brain activity patterns. The human sleep–wake cycle is regulated by the circadian timing system located in the suprachiasmatic nucleus of the hypothalamus. This biological clock coordinates sleep patterns with environmental light–dark cycles [30]. Disruption of circadian rhythms—often caused by irregular work schedules or excessive nighttime light exposure—can significantly impair sleep regulation.

Another widely accepted explanation for insomnia is the hyperarousal model, which proposes that individuals with insomnia exhibit elevated physiological and cognitive activation during periods when the body should normally transition into sleep [31]. This hyperarousal state may involve increased metabolic activity, heightened sympathetic nervous system activation, and persistent cognitive rumination.

Hormonal imbalances also contribute to sleep disturbances. Melatonin, a hormone released by the pineal gland, regulates sleep onset and circadian timing. Reduced melatonin production or delayed secretion can disrupt sleep initiation. Conversely, elevated cortisol levels associated with stress may inhibit the body's ability to enter restful sleep states [32]. Table II summarizes major physiological mechanisms associated with insomnia.

TABLE II: Major physiological mechanisms associated with insomnia

Mechanism	Impact on Sleep
Circadian Rhythm Disruption	Delayed or irregular sleep timing
Hyperarousal State	Increased brain and metabolic activity
Hormonal Imbalance	Reduced melatonin, elevated cortisol
Autonomic Nervous Activation	Elevated heart rate and alertness
Neurotransmitter Dysregulation	Altered serotonin and GABA levels

E. Health Consequences of Chronic Insomnia

Persistent insomnia is associated with numerous long-term health complications that extend beyond sleep disturbances alone. Several longitudinal studies have demonstrated that chronic insomnia significantly increases the risk of cardiovascular disease, including hypertension and coronary artery disease [33]. Sleep deprivation also interferes with glucose metabolism and insulin sensitivity, thereby increasing the likelihood of developing type 2 diabetes [34].

Mental health consequences represent another critical dimension of chronic insomnia. Numerous studies have identified a strong association between insomnia and depressive disorders, suggesting that persistent sleep disturbances may act as both a precursor and a symptom of depression [35]. Furthermore, insomnia has been linked to impaired immune function, making individuals more susceptible to infections and inflammatory diseases [36]. Cognitive decline, particularly in older adults, has also been associated with long-term sleep deprivation [37].

To illustrate global trends in insomnia prevalence during the past two decades, Fig. 4 presents a representative trend plot for selected countries based on epidemiological survey data reported in sleep research literature.

Overall, the growing prevalence of insomnia combined with its substantial health consequences underscores the need for improved detection, monitoring, and preventive strategies. Understanding the clinical characteristics and biological mechanisms of insomnia forms the foundation for developing predictive models and intelligent health systems capable of identifying individuals at risk before chronic sleep disorders emerge.

III. Lifestyle Factors Affecting Sleep

Modern society has witnessed profound lifestyle transformations driven by technological progress, urbanization, and evolving work patterns. These changes have significantly altered daily behavioral routines, which in turn influence sleep quality and circadian rhythm regulation. Lifestyle-related determinants are increasingly recognized as major contributors to insomnia prevalence worldwide. Unlike genetic or medical causes of sleep disorders, lifestyle factors are modifiable, making them critical targets for prevention strategies and predictive health systems. Numerous epidemiological investigations have shown that behavioral habits such as excessive digital

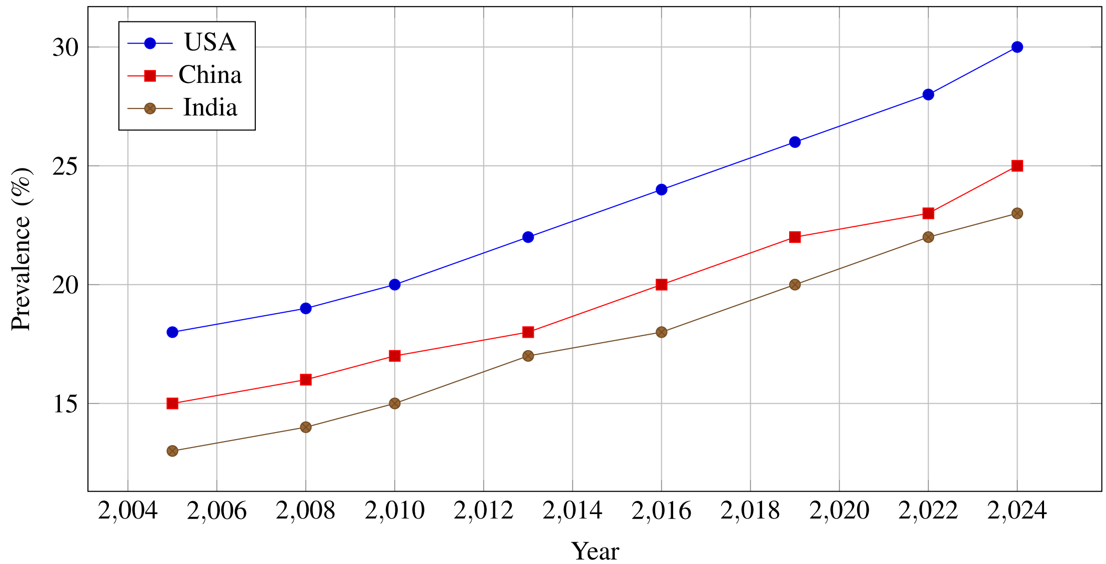

Fig. 4: Representative trends in insomnia prevalence across selected countries over the past two decades.

device use, irregular work schedules, poor dietary patterns, sedentary lifestyles, and psychological stress play a crucial role in disrupting healthy sleep cycles [38]. Understanding the interaction between these lifestyle determinants and sleep physiology is essential for designing effective interventions and predictive frameworks.

A. Digital Lifestyle and Screen Exposure

The widespread adoption of digital technologies has introduced new behavioral patterns that significantly influence sleep behavior. Smartphones, laptops, tablets, and other digital devices have become integral components of daily life, particularly among adolescents and working professionals. While these technologies facilitate communication and productivity, excessive digital engagement during nighttime hours has been strongly associated with sleep disturbances.

One of the primary mechanisms through which digital exposure affects sleep is blue light emission from electronic screens. Blue wavelengths suppress melatonin secretion in the pineal gland, thereby delaying the onset of sleep and altering circadian rhythms [39]. Individuals who frequently engage in late-night internet activities or social media interactions often experience prolonged sleep latency and reduced total sleep duration.

Social media platforms further contribute to sleep disruption through psychological stimulation and emotional engagement. Continuous exposure to notifications, online conversations, and digital entertainment can maintain cognitive arousal at levels incompatible with normal sleep initiation [40]. Empirical studies have reported that individuals who spend more than three hours per day on smartphones are significantly more likely to report symptoms of insomnia compared to those with moderate device usage [41]. These findings highlight the importance of managing digital habits as part of sleep health interventions.

Figure 5 presents a conceptual taxonomy of lifestyle factors that influence sleep quality.

B. Work Schedule and Occupational Stress

Occupational demands represent another major contributor to sleep disturbances. In many modern industries, employees are required to work irregular schedules, night shifts, or extended working hours. Such work patterns disrupt the body's natural circadian rhythm, which is synchronized with the environmental light–dark cycle [42]. Shift workers are particularly vulnerable to sleep disorders because their schedules force them to remain active during periods when the body is biologically programmed for rest.

Night duty and rotating shift schedules can significantly reduce sleep duration and impair sleep quality. Research has demonstrated that individuals engaged in rotating shift work exhibit higher levels of fatigue, reduced cognitive performance, and increased risk of insomnia compared to daytime workers [43]. Additionally, occupational stress and heavy workload can elevate cortisol levels, which further inhibit sleep initiation and maintenance [44]. Over time, chronic sleep deprivation resulting from work-related stress may lead to serious health complications, including cardiovascular disease and metabolic disorders.

C. Diet and Caffeine Consumption

Dietary habits also play a crucial role in regulating sleep patterns. Caffeine, one of the most widely consumed psychoactive substances in the world, acts as a stimulant by blocking adenosine receptors in the brain. While moderate caffeine intake may improve alertness during daytime activities, excessive consumption—especially during evening hours—can significantly delay sleep onset [45].

Alcohol consumption presents a more complex relationship with sleep. Although alcohol may initially induce drowsiness,

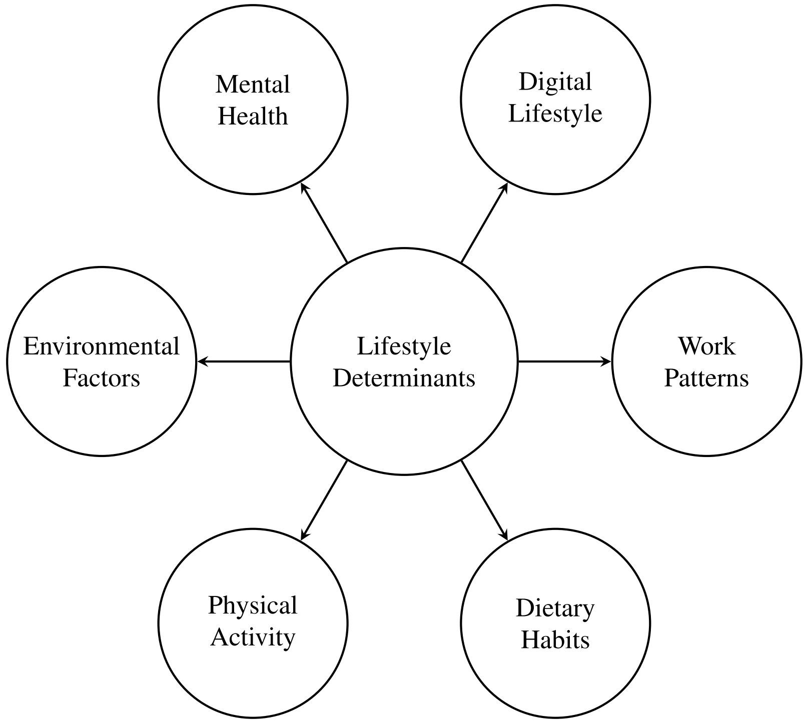

Fig. 5: Circular taxonomy of lifestyle factors influencing sleep quality.

it disrupts the later stages of the sleep cycle, leading to fragmented sleep and reduced rapid eye movement (REM) sleep [46]. Similarly, late-night meals and diets high in sugar content may interfere with metabolic processes that regulate sleep–wake cycles [47]. Nutritional imbalances can also affect neurotransmitter production, thereby influencing mood stability and sleep quality.

D. Physical Activity and Sedentary Behavior

Regular physical activity is widely recognized as a beneficial factor for maintaining healthy sleep patterns. Exercise promotes thermoregulation, enhances metabolic balance, and reduces stress levels, all of which contribute to improved sleep quality [48]. Individuals who engage in moderate physical activity often report shorter sleep latency and deeper sleep stages compared to those with sedentary lifestyles.

Conversely, sedentary behavior—characterized by prolonged periods of sitting and minimal physical movement—has been linked to poor sleep efficiency and increased insomnia symptoms [49]. Urbanization and technology-driven lifestyles have significantly reduced daily physical activity levels in many populations, contributing to the growing prevalence of sleep disorders.

E. Psychological and Mental Health Factors

Psychological factors represent one of the strongest predictors of insomnia. Emotional stress, anxiety, and depressive symptoms frequently interfere with the ability to initiate and maintain sleep. Cognitive hyperarousal—defined as excessive mental activity and persistent worry during nighttime hours—is commonly observed among individuals experiencing insomnia [50].

Anxiety disorders often lead to heightened physiological arousal and increased sympathetic nervous system activity, making it difficult for the body to transition into a restful state [51]. Depression, on the other hand, may alter circadian rhythm regulation and reduce the stability of sleep architecture [52]. These psychological factors are closely intertwined with lifestyle habits such as digital overuse and occupational stress, creating a multifaceted network of influences on sleep health.

Figure 6 illustrates the interaction between lifestyle behaviors and insomnia risk.

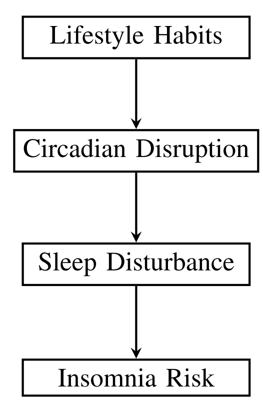

Fig. 6: Flowchart illustrating the relationship between lifestyle behaviors and insomnia risk.

F. Environmental and Social Factors

Environmental conditions within the sleeping environment also influence sleep quality. Noise pollution, excessive light exposure, and uncomfortable room temperatures can interfere with the body's ability to maintain stable sleep cycles [53]. Urban environments often expose individuals to higher levels of nighttime noise and artificial illumination, which may disrupt circadian rhythm synchronization.

Social behaviors such as irregular social schedules, late-night entertainment activities, and inconsistent bedtime routines can further contribute to sleep disturbances [54]. These environmental and social influences often interact with other lifestyle determinants, reinforcing the complexity of insomnia etiology.

Table III presents representative statistics illustrating the prevalence of lifestyle-related sleep risk factors across selected countries during the past two decades.

TABLE III: Representative lifestyle-related sleep risk factors across selected countries

Country	2005 (%)	2015 (%)	2024 (%)
USA	22	27	31
China	18	23	28
India	16	21	26
UK	20	25	30
Japan	24	29	33

Overall, the evidence clearly indicates that lifestyle behaviors exert a substantial influence on sleep quality and insomnia prevalence. As digital technologies continue to reshape daily routines and occupational structures evolve, understanding these behavioral determinants becomes increasingly important. Integrating lifestyle monitoring with predictive health models may provide new opportunities for early detection and prevention of insomnia.

IV. Existing Methods for Insomnia Detection

The identification and monitoring of insomnia have traditionally relied on a combination of clinical evaluation, subjective assessments, and physiological monitoring techniques. Over the past few decades, advancements in biomedical sensing technologies and digital health systems have significantly transformed the methods used to detect sleep disturbances. Conventional clinical procedures such as polysomnography remain the gold standard for sleep analysis, whereas newer approaches incorporate wearable devices, digital questionnaires, and sensor-based monitoring platforms. These methods collectively aim to quantify sleep quality, identify abnormalities in sleep architecture, and support clinicians in diagnosing insomnia and other sleep-related disorders.

A. Clinical Diagnostic Methods

Clinical diagnosis of insomnia generally begins with structured medical evaluations conducted by sleep specialists. The most widely accepted diagnostic method is *polysomnography (PSG)*, an overnight laboratory-based procedure that simultaneously records multiple physiological signals including electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), heart rate, and respiratory patterns. These signals enable clinicians to analyze sleep stages, arousal events, and disruptions in sleep continuity. PSG is considered the reference standard because EEG signals provide direct information about brain activity and sleep stage transitions [55], [56].

Despite its high diagnostic accuracy, PSG has several practical limitations. The procedure requires specialized equipment, trained technicians, and overnight monitoring in sleep laboratories, which can increase costs and limit accessibility for large-scale population studies. Additionally, the presence of multiple sensors attached to the patient may influence natural sleep behavior, thereby introducing potential biases in the recorded data [57]. As a result, PSG is typically reserved for complex sleep disorders or detailed clinical investigations rather than routine insomnia screening.

In addition to PSG, clinicians frequently rely on structured interviews and medical history assessments to identify insomnia symptoms. During these interviews, patients report difficulties related to sleep onset, sleep maintenance, or early morning awakenings. Physicians evaluate these symptoms alongside lifestyle factors, mental health conditions, and comorbid diseases to determine the severity and potential causes of insomnia [58]. Although clinical interviews provide valuable contextual information, they remain subjective and depend heavily on patient self-reporting.

B. Questionnaire-Based Assessments

Questionnaire-based tools represent one of the most widely used approaches for evaluating sleep quality and insomnia severity in both clinical practice and research studies. These instruments provide standardized scoring mechanisms that allow clinicians and researchers to quantify sleep disturbances across large populations.

One of the most commonly used instruments is the *Pittsburgh Sleep Quality Index (PSQI)*, which evaluates sleep quality over a one-month period through multiple components including sleep latency, sleep duration, disturbances, and daytime dysfunction. PSQI scores provide a global index of sleep quality and are widely used in epidemiological studies investigating lifestyle-related sleep disorders [59].

Another widely adopted tool is the *Insomnia Severity Index (ISI)*, which specifically measures the perceived severity of insomnia symptoms such as difficulty falling asleep, sleep dissatisfaction, and the impact of sleep problems on daily functioning. The ISI questionnaire is particularly useful for assessing treatment outcomes and monitoring improvements in sleep behavior over time [60].

Similarly, the *Epworth Sleepiness Scale (ESS)* evaluates daytime sleepiness by measuring the likelihood of falling asleep in different everyday situations. Although ESS does not directly diagnose insomnia, it provides valuable insights into excessive daytime sleepiness associated with poor sleep quality [61].

While questionnaire-based assessments are easy to administer and cost-effective, they rely on subjective self-reported data. Consequently, these tools may be influenced by recall bias, emotional factors, or individual perception of sleep quality. For this reason, many clinical studies combine questionnaires with objective monitoring techniques to obtain more reliable sleep measurements.

C. Wearable and Sensor-Based Monitoring

Recent advancements in digital health technologies have enabled the development of wearable and sensor-based systems capable of continuously monitoring sleep patterns in real-world environments. These technologies provide a promising alternative to laboratory-based sleep studies by enabling long-term sleep tracking in natural settings.

One of the most widely used technologies in sleep monitoring is *actigraphy*. Actigraphy devices typically resemble wristwatches and use accelerometers to measure body movements during sleep and wake periods. By analyzing activity patterns, actigraphy can estimate sleep duration, sleep efficiency, and circadian rhythm patterns. Compared to polysomnography, actigraphy offers a more convenient and cost-effective method for long-term sleep monitoring, particularly in large population studies [62]. However, actigraphy may overestimate sleep duration because it interprets periods of inactivity as sleep, even when individuals remain awake but motionless [55].

Smart wearable devices such as smartwatches and fitness trackers have further expanded sleep monitoring capabilities. These devices integrate multiple sensors, including accelerometers, photoplethysmography (PPG), and temperature sensors, to track physiological signals such as heart rate variability and body movement. Machine learning algorithms can analyze these signals to estimate sleep stages and detect sleep disturbances [63]. The ability of wearable devices to collect continuous physiological data makes them particularly valuable for identifying lifestyle factors that influence sleep quality.

Another emerging technology involves wearable electroencephalography (EEG) devices designed for home-based sleep monitoring. These systems use compact electrodes placed on the forehead or scalp to record brain activity and approximate sleep stages. Recent studies have demonstrated that wearable EEG devices can achieve moderate to substantial agreement with traditional polysomnography, suggesting their potential use in large-scale sleep monitoring applications [64]. In addition, multimodal sensor platforms combining accelerometers, ECG signals, and skin temperature measurements have been explored to automatically classify sleep states and detect sleep disruptions [65].

The integration of wearable sensors with mobile health platforms also enables real-time sleep tracking and personalized health insights. These systems can continuously collect sleep-related data and provide feedback through smartphone applications, allowing individuals to monitor their sleep habits and adopt healthier lifestyles. Although wearable technologies show considerable promise, challenges remain regarding accuracy, data privacy, and clinical validation.

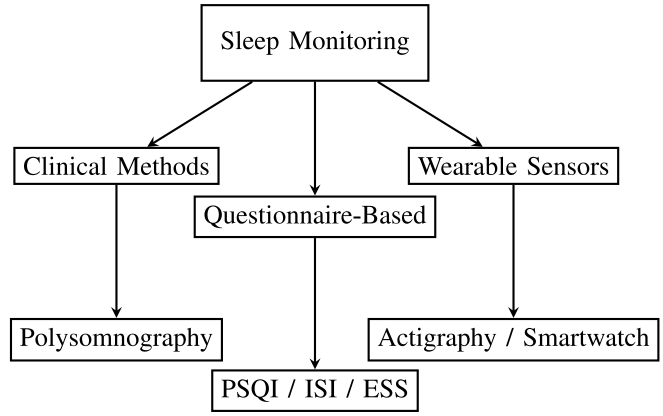

Fig. 7: Taxonomy of existing insomnia detection methods

V. Machine Learning Approaches for Insomnia Prediction

In recent years, machine learning techniques have increasingly been explored for predicting insomnia and identifying sleep disturbances associated with modern lifestyle patterns. Unlike traditional clinical assessments that rely primarily on episodic observations or self-reported questionnaires, machine learning models enable continuous analysis of behavioral and physiological data collected from digital devices. These computational models can discover hidden correlations between lifestyle habits and sleep outcomes, allowing early detection of insomnia risk factors. As a result, predictive analytics has become an important research direction in digital health and sleep medicine, supporting the development of personalized sleep monitoring systems and preventive healthcare strategies.

A. Data Sources for Prediction Models

The effectiveness of machine learning models for insomnia prediction largely depends on the diversity and quality of the input data. Modern predictive systems often rely on multimodal datasets collected from wearable devices, mobile applications, and lifestyle surveys. One of the most common data sources is wearable sleep monitoring data, which is obtained from devices such as smartwatches and fitness trackers. These devices record continuous physiological signals including heart rate variability, body movement, and sleep duration. Such data provide valuable insights into sleep–wake cycles and circadian rhythm patterns [66].

Another important source of information is lifestyle survey data collected through questionnaires or digital health platforms. These surveys typically capture behavioral factors such as work schedules, physical activity levels, dietary habits, and perceived stress. Several studies have demonstrated that lifestyle patterns significantly influence sleep quality, making these datasets useful for predictive modeling [67].

TABLE IV: Comparison of Existing Insomnia Detection Methods

Method	Data Type	Advantages	Limitations
Polysomnography (PSG)	EEG, EOG, EMG	High accuracy	Expensive, laboratory based
Clinical Interviews	Patient history	Contextual diagnosis	Subjective reporting
Sleep Questionnaires	Survey responses	Easy to administer	Recall bias
Actigraphy	Motion signals	Long-term monitoring	Cannot detect sleep stages
Wearable Sensors	Multimodal signals	Continuous monitoring	Accuracy varies

Smartphone usage logs also represent an emerging source of behavioral data for sleep prediction. Screen exposure before bedtime, late-night device interaction, and irregular usage patterns have been associated with delayed sleep onset and disrupted circadian rhythms. Machine learning models can analyze these digital activity patterns to estimate the probability of insomnia or sleep deprivation [68]. In addition, physiological signals such as electroencephalography (EEG), electrocardiography (ECG), and respiration rate measurements are sometimes integrated into predictive frameworks to improve model reliability and provide objective indicators of sleep disturbances.

B. Feature Engineering for Sleep Prediction

Feature engineering plays a crucial role in transforming raw sleep-related data into meaningful variables that can be used by machine learning algorithms. Sleep duration is one of the most fundamental features, as insufficient sleep has been consistently associated with cognitive impairment, fatigue, and increased insomnia risk. Similarly, sleep latency, defined as the time required to transition from wakefulness to sleep, provides an important indicator of sleep initiation difficulties [69].

Another relevant feature is physical activity level, which can be estimated from accelerometer data collected by wearable devices. Moderate daily physical activity is generally associated with improved sleep efficiency, whereas sedentary lifestyles may contribute to irregular sleep patterns. Screen time before bedtime is also considered a significant behavioral predictor because prolonged exposure to blue light emitted from electronic devices can suppress melatonin production and delay sleep onset.

Dietary habits further influence sleep patterns, particularly the consumption of caffeine and stimulants during evening hours. Machine learning models often include caffeine intake as a feature because excessive consumption has been linked to fragmented sleep and increased nighttime awakenings. In addition, psychological stress levels measured through surveys or physiological markers such as heart rate variability are incorporated into predictive models to capture the interaction between mental health and sleep quality. By combining these behavioral and physiological indicators, feature engineering enables machine learning algorithms to learn complex patterns that contribute to insomnia development.

C. Machine Learning Models Used in Literature

Various machine learning algorithms have been applied to predict insomnia risk and classify sleep disturbances. Traditional statistical learning models are often used as baseline approaches due to their interpretability and computational efficiency. Logistic regression models have been widely adopted to estimate the probability of insomnia occurrence based on lifestyle variables and demographic factors. These models provide interpretable coefficients that help identify key risk factors associated with sleep disorders [70].

Decision tree algorithms represent another commonly used method for insomnia prediction. These models generate hierarchical decision rules that partition the dataset based on relevant sleep-related features such as sleep duration, activity level, and caffeine intake. Ensemble techniques such as Random Forest further enhance predictive performance by aggregating multiple decision trees and reducing model variance. Support Vector Machines (SVM) have also been employed to classify sleep disorders by constructing optimal hyperplanes that separate insomnia cases from healthy sleep patterns.

In addition to these traditional methods, deep learning architectures have gained significant attention for modeling complex temporal relationships within sleep data. Convolutional Neural Networks (CNN) are particularly useful for analyzing physiological signals such as EEG or actigraphy data because they can automatically extract spatial patterns from high-dimensional inputs. Recurrent neural networks, especially Long Short-Term Memory (LSTM) models, are designed to capture temporal dependencies in sequential data such as sleep cycles recorded across multiple nights [71]. Hybrid architectures that combine CNN and LSTM layers have also been proposed to simultaneously learn spatial features from physiological signals and temporal trends in sleep behavior, leading to improved predictive accuracy.

D. Performance Evaluation Metrics

The evaluation of machine learning models for insomnia prediction requires appropriate performance metrics to measure classification effectiveness and generalization capability. Accuracy is one of the most commonly used metrics and represents the proportion of correctly predicted instances among the total number of observations. Although accuracy provides a general measure of performance, it may be insufficient when dealing with imbalanced datasets where insomnia cases are less frequent.

Precision and recall are therefore frequently used to provide a more detailed evaluation. Precision measures the proportion of correctly identified insomnia cases among all predicted positive cases, while recall indicates the ability of the model to detect actual insomnia occurrences. The F1-score, which represents the harmonic mean of precision and recall, provides

TABLE V: Common Machine Learning Models Used for Insomnia Prediction

Model	Category	Key Advantage
Logistic Regression	Traditional ML	High interpretability
Decision Tree	Traditional ML	Easy rule extraction
Random Forest	Ensemble ML	Improved accuracy and robustness
Support Vector Machine	Traditional ML	Effective for high-dimensional data
CNN	Deep Learning	Automatic feature extraction from signals
LSTM	Deep Learning	Captures temporal sleep patterns
CNN-LSTM	Hybrid Model	Combines spatial and temporal learning

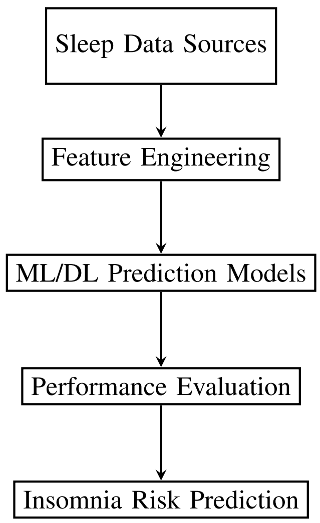

Fig. 8: General workflow of machine learning-based insomnia prediction systems

a balanced evaluation when both false positives and false negatives are important considerations.

Another widely used metric is the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). This metric evaluates the ability of the model to distinguish between insomnia and non-insomnia cases across different classification thresholds. A higher ROC-AUC value indicates stronger discriminative capability and better overall predictive performance. These evaluation measures collectively enable researchers to compare different machine learning algorithms and identify the most effective models for insomnia forecasting.

VI. Comparative Analysis of Existing Studies

Over the past two decades, research on insomnia detection and prediction has expanded significantly due to the increasing availability of digital health data and advances in computational intelligence. Early investigations primarily relied on clinical observations and small-scale experimental studies, whereas recent research increasingly utilizes wearable sensing devices, smartphone interaction logs, and large behavioral datasets. This shift has enabled researchers to apply machine learning and deep learning techniques for identifying complex patterns associated with sleep disturbances. Despite these technological developments, the literature reveals considerable variation in datasets, feature engineering strategies, algorithmic choices, and reported predictive performance.

A major difference among existing studies lies in the type and scale of datasets used for insomnia detection. Some studies rely on physiological signals collected through wearable devices such as actigraphy sensors and smartwatches. These datasets typically contain continuous measurements of body movement, heart rate variability, and sleep duration. Although such physiological datasets provide objective indicators of sleep patterns, they often require specialized hardware and controlled monitoring environments, which may limit their scalability for large population studies.

Other research efforts have focused on survey-based or lifestyle datasets. These datasets generally include behavioral variables such as caffeine intake, work schedules, screen exposure before bedtime, and self-reported stress levels. Lifestyle datasets are easier to collect and can capture contextual information that is difficult to measure using physiological sensors alone. However, they may also introduce biases due to subjective reporting or inconsistent data recording.

Algorithm selection represents another key factor influencing predictive performance in insomnia research. Traditional machine learning models such as Support Vector Machines, Decision Trees, and Random Forest classifiers have been widely adopted due to their interpretability and relatively low computational complexity. These models perform well when the feature space is carefully engineered and the dataset size is moderate. Ensemble learning techniques, particularly Random Forest models, have demonstrated improved predictive stability by aggregating the outputs of multiple decision trees.

More recently, deep learning methods have been explored to analyze high-dimensional physiological signals such as EEG recordings and actigraphy time series. Convolutional Neural Networks (CNNs) are capable of extracting hierarchical features from signal data without extensive manual feature engineering. Similarly, Long Short-Term Memory (LSTM) networks are effective for modeling temporal dependencies in sleep cycle sequences. Hybrid architectures that combine CNN and LSTM layers have shown promising results in predicting sleep disorders from multi-night monitoring data. Nevertheless, deep learning models often require large labeled datasets and substantial computational resources, which may limit their applicability in real-world clinical settings.

Performance evaluation across studies also varies depending on the metrics used and the characteristics of the datasets. While many studies report classification accuracy as the primary performance indicator, additional metrics such as precision, recall, F1-score, and area under the ROC curve are

TABLE VI: Comparative Analysis of Existing Studies on Insomnia Detection and Prediction

Study	Dataset Type	Features Used	Algorithm	Accuracy	Key Limitation
Study A	Wearable actigraphy data	Activity level, heart rate	SVM	84%	Small sample size
Study B	Lifestyle survey data	Diet, screen time, stress	Random Forest	88%	Limited physiological data
Study C	EEG sensor recordings	Brainwave signals	CNN	92%	Expensive hardware requirement
Study D	Smartphone usage logs	Screen time, usage frequency	Logistic Regression	80%	Behavioral data only
Study E	Wearable + survey data	Activity, sleep duration, stress	Decision Tree	86%	Limited temporal modeling
Study F	Multi-night sleep recordings	EEG + movement signals	CNN-LSTM	93%	High computational cost
Study G	Population sleep survey	Lifestyle variables	SVM	82%	Self-report bias
Study H	Smartwatch data	HR variability, sleep stages	Random Forest	90%	Device variability

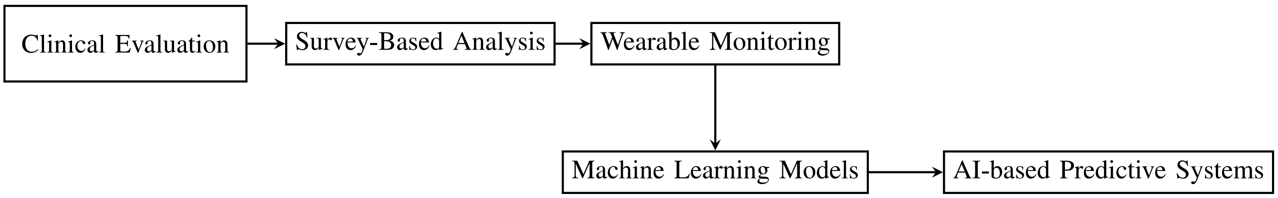

Fig. 9: Evolution of insomnia detection approaches from traditional clinical assessment to AI-driven predictive systems

frequently used to provide a more comprehensive evaluation. In cases where insomnia prevalence is relatively low within the dataset, relying solely on accuracy may produce misleading results because models can achieve high accuracy simply by predicting the majority class.

Beyond performance differences, several limitations appear consistently across existing research. Many studies are conducted using relatively small datasets obtained from specific demographic groups such as university students or healthcare workers. Consequently, the generalizability of these predictive models to broader populations remains uncertain. Furthermore, several approaches focus exclusively on physiological signals without incorporating lifestyle behaviors, even though behavioral factors such as digital device usage and occupational stress have been shown to significantly influence sleep quality. These limitations highlight the need for integrated predictive frameworks that combine physiological monitoring with lifestyle-based behavioral analytics.

To better understand the methodological diversity in the literature, Table VI summarizes representative studies on insomnia detection and prediction. The table compares key aspects including dataset type, feature categories, applied algorithms, achieved accuracy, and identified limitations. This comparative overview highlights both the progress made in predictive sleep analytics and the challenges that remain for future research.

In addition to tabular comparisons, the evolution of insomnia prediction methodologies can be conceptualized as a progression from traditional clinical assessment to data-driven computational modeling. Figure 9 illustrates this transition and highlights how modern predictive systems integrate multiple data sources and artificial intelligence algorithms.

Overall, the comparative analysis indicates that although significant progress has been made in applying computational methods for insomnia prediction, several challenges remain unresolved. These include the lack of standardized datasets, limited integration of lifestyle factors, and insufficient validation across diverse demographic populations. Addressing these issues is essential for developing reliable predictive models that can support early detection and personalized management of insomnia in real-world healthcare environments.

VII. Research Gaps

Although considerable progress has been achieved in the study of insomnia detection and prediction, the existing literature reveals several unresolved challenges that limit the reliability, scalability, and practical adoption of current approaches. Recent advances in artificial intelligence and wearable sensing technologies have opened new opportunities for sleep analytics; however, many proposed models remain experimental and are rarely integrated into real clinical environments. Systematic reviews in sleep medicine indicate that only a small subset of published studies meet rigorous validation standards, highlighting the need for more comprehensive research frameworks [72]. Furthermore, the rapid growth of digital lifestyle behaviors, including prolonged smartphone usage and irregular work schedules, has introduced complex behavioral variables that are not yet fully incorporated into predictive sleep models.

One of the most prominent limitations in current research is the **lack of integrated lifestyle datasets**. Most studies rely either on physiological data obtained from polysomnography or actigraphy sensors, or on self-reported lifestyle surveys. While physiological signals provide objective measurements of sleep patterns, lifestyle datasets capture contextual behavioral factors such as diet, stress, and digital device exposure. However, these data sources are typically studied independently, resulting in fragmented analytical frameworks. As a result, many predictive models fail to capture the complex interactions between behavioral, psychological, and physiological determinants of insomnia. Existing literature emphasizes that comprehensive multimodal datasets combining demographic, behavioral, and physiological variables remain scarce [73].

Another significant research gap concerns the **limited availability of long-term insomnia forecasting models**. Most existing machine learning studies focus on short-term classification tasks, such as determining whether an individual currently exhibits insomnia symptoms. These models are generally trained on cross-sectional datasets or short monitoring periods. Consequently, they lack the ability to forecast future insomnia risk based on evolving lifestyle behaviors. Longitudinal monitoring of sleep patterns is essential for identifying early warning signals of chronic sleep disorders, yet only a few studies utilize long-duration wearable datasets for predictive analysis. In many cases, missing data and inconsistent monitoring intervals further complicate the development of reliable longitudinal prediction models [74].

A further limitation in the literature is the **limited use of multimodal data sources** for sleep analysis. Although sleep physiology is influenced by multiple biological and environmental factors, many existing studies rely on a single type of input signal, particularly electroencephalography (EEG) recordings. Reviews of sleep stage classification research have reported that only a small fraction of studies utilize multiple physiological signals simultaneously, despite the fact that combining signals such as EEG, electrocardiography (ECG), and actigraphy can significantly improve predictive performance [75]. The reliance on single-channel datasets restricts the ability of predictive systems to capture the full complexity of sleep dynamics.

Another critical challenge is the **absence of real-time insomnia prediction systems** capable of continuous monitoring and early intervention. Current diagnostic procedures typically rely on laboratory-based sleep studies or retrospective data analysis. Although wearable technologies and smartphone-based monitoring platforms have enabled the collection of real-time behavioral data, the integration of these data streams into adaptive prediction systems remains limited. Real-time monitoring frameworks would allow early detection of sleep disturbances and facilitate timely behavioral interventions, thereby reducing the long-term health consequences associated with chronic insomnia.

The issue of **explainability and transparency in artificial intelligence models** also represents a major research challenge. Many deep learning approaches used for sleep disorder prediction operate as black-box systems that provide high predictive accuracy but limited interpretability. In clinical contexts, healthcare professionals require clear explanations regarding how predictive models reach their decisions. Without transparent reasoning mechanisms, clinicians may be reluctant to rely on automated predictions for medical decision-making. Recent research highlights the growing importance of explainable artificial intelligence (XAI) methods such as SHAP and LIME to improve model transparency and facilitate trust in AI-driven healthcare systems [76]. Nevertheless, only a small proportion of insomnia prediction studies currently incorporate explainability mechanisms into their modeling frameworks.

Beyond methodological limitations, issues related to **data bias and generalizability** also remain insufficiently addressed. Many datasets used for sleep research are collected from specific demographic groups, such as university students, hospital patients, or individuals from a single geographic region. Consequently, predictive models trained on such datasets may not generalize effectively across diverse populations. Additionally, variations in lifestyle habits, cultural behaviors, and environmental conditions can significantly influence sleep patterns. Addressing these challenges requires the development of large-scale, multi-center datasets that capture diverse demographic and geographic characteristics.

To summarize the key research gaps identified in the literature, Table VII provides a structured comparison of current limitations and potential research opportunities for future insomnia prediction systems.

To further conceptualize these limitations, Figure 10 illustrates the major gaps identified in current insomnia research and their relationship with future predictive healthcare systems.

Overall, the analysis of existing studies demonstrates that although machine learning has significantly improved the detection of sleep disorders, several methodological and practical limitations remain unresolved. Addressing these gaps requires interdisciplinary collaboration between sleep medicine researchers, data scientists, and healthcare practitioners. The integration of multimodal datasets, explainable artificial intelligence techniques, and real-time monitoring platforms has the potential to transform insomnia prediction from retrospective diagnosis into proactive and personalized sleep health management.

VIII. Proposed Predictive Framework

The growing influence of digital lifestyles, wearable technologies, and artificial intelligence has created new opportunities for proactive monitoring of sleep health. Building upon the research gaps identified in the previous section, this review proposes a conceptual predictive framework designed to forecast insomnia risk using integrated lifestyle, behavioral, and physiological data sources. The objective of the proposed framework is not to replace clinical diagnosis but to provide an early-warning analytical system capable of identifying individuals who may be at elevated risk of developing sleep disorders. By combining multi-source data acquisition, robust preprocessing pipelines, advanced feature engineering, and machine learning prediction models, the proposed architecture aims to enable scalable and real-time insomnia risk assessment.

Unlike traditional insomnia studies that rely primarily on laboratory-based measurements, the proposed framework emphasizes continuous monitoring of lifestyle behaviors that influence sleep quality. Modern wearable devices, smartphones, and digital health platforms generate large volumes of behavioral data that can be leveraged to model sleep-related patterns. Integrating these heterogeneous data streams within a unified prediction pipeline allows the development of more comprehensive insomnia forecasting systems capable of identifying early behavioral signals associated with sleep disruption.

TABLE VII: Major Research Gaps in Current Insomnia Prediction Studies

Research Aspect	Current Limitation	Future Research Direction
Data Integration	Physiological and lifestyle datasets analyzed separately	Development of integrated multimodal sleep datasets
Prediction Scope	Short-term classification dominates existing studies	Longitudinal forecasting of insomnia risk
Data Modalities	Predominant reliance on single-channel EEG data	Integration of multiple signals (EEG, ECG, actigraphy)
Monitoring Systems	Limited real-time monitoring frameworks	Continuous wearable-based predictive systems
Model Transparency	Black-box deep learning models	Explainable AI approaches for clinical trust
Dataset Diversity	Small, geographically limited samples	Multi-center global sleep datasets

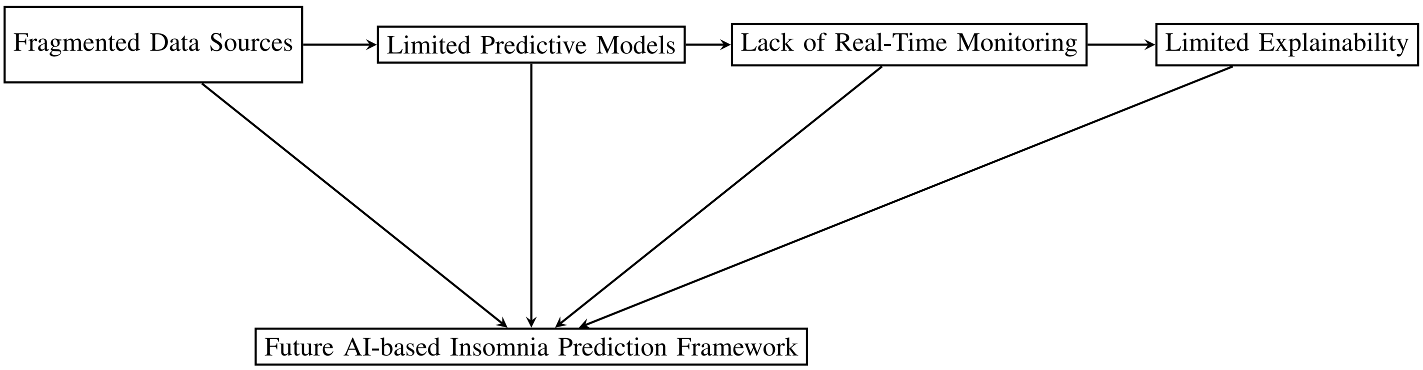

Fig. 10: Conceptual illustration of major research gaps and their connection to future AI-driven insomnia prediction systems

A. Lifestyle Data Collection

The first stage of the proposed framework focuses on collecting diverse lifestyle and physiological data relevant to sleep patterns. Multiple sources can be integrated to capture both objective and behavioral indicators of sleep quality.

Wearable devices such as smartwatches and fitness trackers provide continuous physiological monitoring, including heart rate variability, sleep duration, and physical activity levels. These devices can automatically record sleep stages and movement patterns during nighttime rest periods. In parallel, smartphone sensors and digital activity logs can provide valuable behavioral information such as screen exposure before bedtime, application usage patterns, and nighttime device interactions.

Lifestyle surveys represent another important data source that can capture contextual information not easily measurable through sensors. These surveys may include questions related to caffeine consumption, dietary habits, occupational stress levels, work schedules, and mental health indicators. Combining sensor-derived data with self-reported lifestyle variables allows a more holistic representation of factors influencing sleep quality.

Table VIII summarizes the primary data sources and the types of features collected for insomnia prediction.

B. Data Preprocessing

Raw data collected from heterogeneous sources often contains noise, missing values, and inconsistencies that can negatively affect predictive model performance. Therefore, a comprehensive preprocessing stage is required to transform raw datasets into structured analytical inputs.

Noise removal techniques are applied to eliminate irregular sensor readings or erroneous measurements generated by wearable devices. Missing value handling strategies, including interpolation or statistical imputation methods, are employed to ensure data completeness. Since the collected variables may have different numerical ranges, normalization or standardization techniques are applied to scale the data into comparable ranges.

Furthermore, temporal alignment is necessary when combining datasets collected at different sampling frequencies. Synchronizing timestamps from wearable devices, smartphone logs, and lifestyle records ensures accurate temporal representation of behavioral patterns affecting sleep.

C. Feature Extraction

After preprocessing, relevant features are extracted to represent patterns associated with sleep behavior. Feature engineering plays a critical role in improving predictive model performance because it enables the transformation of raw signals into meaningful indicators of insomnia risk.

Sleep duration patterns are among the most informative features and can include metrics such as average sleep time, variability in sleep duration, and frequency of nighttime awakenings. Behavioral indicators derived from smartphone activity logs can capture late-night digital engagement, which has been shown to influence sleep onset latency.

Physiological features derived from wearable sensors may include heart rate variability, physical activity levels during daytime, and circadian rhythm indicators. Combining physiological signals with behavioral indicators allows predictive models to capture both biological and lifestyle determinants of sleep quality.

D. Machine Learning Prediction Engine

The central component of the proposed framework is the machine learning prediction engine responsible for modeling

TABLE VIII: Data Sources for Lifestyle-Based Insomnia Prediction

Source	Data Type	Example Features
Wearable Devices	Physiological Signals	Sleep duration, heart rate, activity level
Smartphone Sensors	Behavioral Data	Screen time, app usage, nighttime activity
Lifestyle Surveys	Self-reported Data	Stress level, diet habits, caffeine intake
Environmental Sensors	Contextual Data	Room temperature, noise level, light exposure

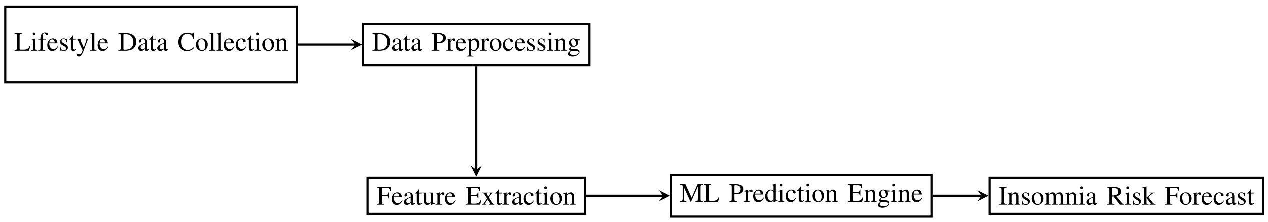

Fig. 11: Conceptual architecture of the proposed lifestyle-based insomnia prediction framework

the relationship between extracted features and insomnia risk. Multiple machine learning approaches can be utilized depending on the nature and size of the dataset.

Traditional models such as Random Forest classifiers are particularly useful for structured lifestyle datasets because they can handle nonlinear relationships and provide robust feature importance measures. Decision tree-based ensemble methods also demonstrate resilience to noisy data and missing values.

For temporal sleep data collected across multiple nights, recurrent neural network architectures such as Long Short-Term Memory (LSTM) networks can capture sequential dependencies in sleep patterns. These models are capable of identifying temporal trends in behavioral or physiological variables that may indicate the gradual onset of sleep disturbances.

Hybrid models combining convolutional layers with recurrent networks may also be employed to simultaneously capture spatial features in physiological signals and temporal dependencies across sleep cycles.

E. Insomnia Risk Forecasting

The final stage of the framework involves generating insomnia risk predictions based on the outputs of the trained machine learning models. Instead of providing binary predictions, the proposed system categorizes individuals into multiple risk levels, enabling more nuanced interpretation of predictive outcomes.

Risk categories can include low-risk individuals who demonstrate stable sleep patterns, moderate-risk individuals who show occasional sleep disturbances, and high-risk individuals whose behavioral and physiological patterns indicate a strong likelihood of developing insomnia.

Such stratified predictions can assist healthcare professionals in prioritizing preventive interventions and recommending lifestyle modifications before chronic sleep disorders emerge.

To illustrate the overall architecture of the proposed framework, Figure 11 presents a conceptual system design integrating data collection, preprocessing, feature extraction, and machine learning prediction stages.

In addition to the system architecture, the operational workflow of the predictive pipeline is illustrated in Figure 12,

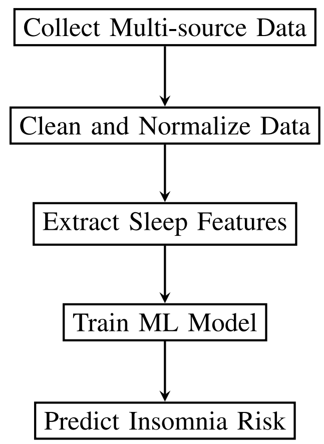

Fig. 12: Workflow of the proposed insomnia prediction pipeline

which describes the sequential data processing stages used to generate insomnia risk predictions.

Overall, the proposed predictive framework integrates behavioral analytics, physiological monitoring, and machine learning techniques to provide a comprehensive platform for insomnia risk forecasting. By leveraging multimodal data sources and advanced predictive models, the framework offers a scalable approach for early detection of sleep disorders. Such systems have the potential to support preventive healthcare strategies and promote healthier sleep behaviors in modern digitally connected societies.

IX. Challenges and Future Research Directions

Despite significant progress in computational sleep analytics and machine learning–based prediction systems, several technical, ethical, and infrastructural challenges continue to limit the practical deployment of insomnia forecasting models. While modern wearable technologies and digital health platforms generate large volumes of behavioral and physiological data, transforming these heterogeneous datasets into reliable and clinically meaningful predictions remains a complex task. Addressing these challenges is essential for developing trustworthy predictive systems capable of supporting early detection and prevention of sleep disorders.

In addition to methodological limitations, broader concerns such as data privacy, dataset availability, algorithm transparency, and integration with healthcare infrastructures play a crucial role in determining the feasibility of real-world insomnia prediction systems. This section discusses the major challenges observed in the current literature and outlines potential future research directions that may enhance the reliability and scalability of lifestyle-based insomnia forecasting frameworks.

A. Data Privacy Issues

One of the most critical challenges in digital sleep monitoring systems involves the protection of sensitive health information. Predictive insomnia models often rely on personal behavioral data collected from wearable devices, smartphone sensors, and lifestyle questionnaires. These datasets may contain highly sensitive information related to sleep habits, mental health conditions, daily routines, and physiological signals. Unauthorized access or misuse of such information could raise serious ethical and legal concerns.

Furthermore, data collected through wearable technologies are frequently stored in cloud-based infrastructures, which introduces additional cybersecurity risks. Ensuring secure data transmission, storage, and processing is therefore essential for protecting user privacy. Future research should focus on developing privacy-preserving data analytics frameworks, including encrypted data pipelines and federated learning approaches. Such techniques enable machine learning models to be trained across distributed datasets without transferring raw personal data, thereby reducing the risk of privacy breaches.

B. Dataset Availability

Another major limitation in insomnia prediction research is the scarcity of large-scale, publicly available datasets. Many existing studies rely on relatively small datasets collected within controlled laboratory environments or specific demographic groups such as university students or healthcare workers. Although these datasets provide valuable insights into sleep patterns, their limited size and population diversity restrict the generalizability of predictive models.

Moreover, sleep-related datasets often lack standardized feature representations, making it difficult to compare results across different studies. Variations in data collection protocols, sensor types, and monitoring durations can significantly affect model performance and reproducibility. Future research efforts should therefore prioritize the development of open-access sleep datasets containing multimodal behavioral and physiological features collected from diverse populations. Establishing standardized benchmarking datasets would also facilitate more reliable evaluation of insomnia prediction algorithms.

C. Model Interpretability

While machine learning and deep learning models have demonstrated promising predictive performance in sleep analytics, their interpretability remains a significant concern in healthcare applications. Many advanced algorithms, particularly deep neural networks, operate as complex black-box systems whose internal decision-making processes are difficult to interpret.

In clinical contexts, healthcare professionals require transparent explanations for predictive outcomes before incorporating algorithmic recommendations into diagnostic or therapeutic decisions. Without interpretable insights, physicians may hesitate to rely on automated insomnia prediction systems. Consequently, future research should focus on integrating explainable artificial intelligence (XAI) techniques into sleep prediction models. Methods such as feature importance analysis, attention mechanisms, and interpretable decision models can help reveal how behavioral or physiological variables contribute to predicted insomnia risk levels.

D. Integration with Digital Health Systems

The long-term success of predictive insomnia monitoring systems will depend largely on their ability to integrate with broader digital healthcare ecosystems. Emerging healthcare technologies such as telemedicine platforms, remote patient monitoring systems, and AI-powered health assistants offer new opportunities for delivering personalized sleep interventions.

For example, insomnia prediction models could be integrated with telemedicine systems to enable remote consultation between patients and sleep specialists. When predictive algorithms detect high insomnia risk, the system could automatically notify healthcare providers and recommend behavioral interventions. Similarly, integration with digital health assistants may allow individuals to receive real-time guidance on sleep hygiene practices, stress management techniques, or lifestyle modifications.

However, achieving such integration requires addressing interoperability challenges between wearable devices, healthcare information systems, and clinical decision-support platforms. Standardized data exchange protocols and collaborative frameworks between technology developers and healthcare providers will be essential for enabling seamless integration.

Table IX summarizes the key challenges identified in insomnia prediction research along with potential future research directions.

To illustrate the relationship between the major research challenges and future technological developments, Figure 13 presents a conceptual overview of the key barriers affecting insomnia prediction systems.

In addition to addressing these challenges, future research may also explore the development of intelligent sleep-health ecosystems capable of continuously monitoring lifestyle behaviors and providing personalized recommendations. Figure 14 illustrates a potential architecture for such an ecosystem integrating wearable devices, machine learning models, and digital healthcare platforms.

Overall, overcoming the challenges discussed above will require interdisciplinary collaboration between data scientists, healthcare professionals, behavioral scientists, and technology

TABLE IX: Major Challenges and Future Research Opportunities in Insomnia Prediction

Challenge	Impact	Future Research Direction
Data Privacy	Risk of personal health data exposure	Privacy-preserving ML and federated learning
Dataset Availability	Limited model generalization	Creation of open multimodal sleep datasets
Model Interpretability	Reduced clinical trust	Explainable AI methods for healthcare
System Integration	Limited clinical deployment	Interoperable digital health platforms

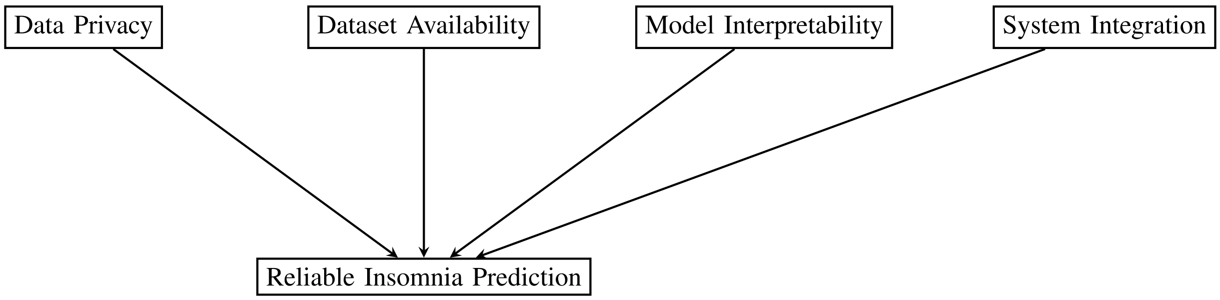

Fig. 13: Key challenges affecting the development of reliable insomnia prediction systems

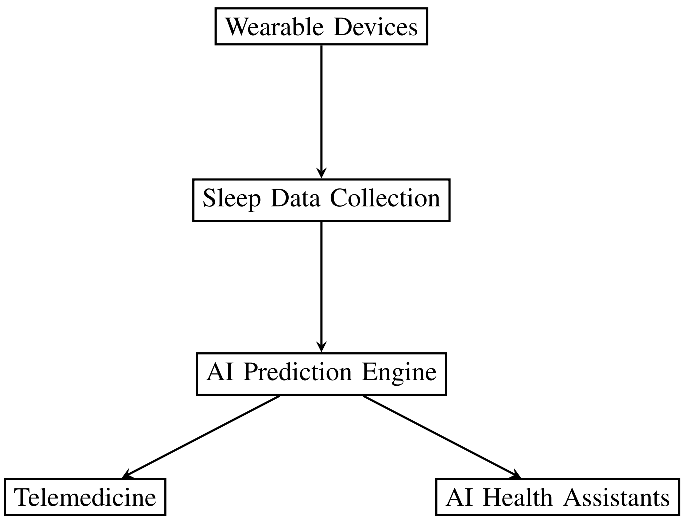

Fig. 14: Future digital health ecosystem for AI-driven insomnia monitoring and intervention

developers. By addressing privacy concerns, expanding dataset availability, improving model transparency, and integrating predictive systems within digital healthcare infrastructures, future research can significantly enhance the reliability and practical adoption of AI-driven insomnia forecasting technologies.

X. Conclusion

Sleep is a fundamental biological process that plays a vital role in maintaining physical health, cognitive performance, and emotional stability. However, the prevalence of insomnia has increased significantly in recent years due to changes in lifestyle behaviors, work patterns, and digital engagement. This review paper examined the existing body of literature on insomnia with a particular emphasis on lifestyle-related determinants and the emerging role of data-driven predictive models. Through a systematic examination of prior studies, the paper highlighted how modern lifestyle characteristics—such as prolonged screen exposure, irregular sleep schedules, psychological stress, sedentary behavior, and dietary patterns—have become important contributors to sleep disturbances across diverse populations.

The analysis of previous research demonstrates that conventional clinical assessment methods for insomnia are gradually being complemented by computational techniques capable of processing large-scale behavioral and physiological data. Machine learning approaches including Support Vector Machines, Random Forest models, and deep learning architectures have shown promising performance in identifying patterns associated with sleep disruption. These models are particularly effective when trained on multimodal datasets that integrate wearable sensor measurements, smartphone-derived behavioral indicators, and self-reported lifestyle information. The comparative analysis presented in this review indicates that predictive accuracy tends to improve when models incorporate both physiological signals and contextual lifestyle features rather than relying on a single source of data.

Another important finding emerging from this study is the increasing feasibility of continuous sleep monitoring through consumer technologies. Wearable devices, smart health platforms, and mobile applications now provide mechanisms for collecting longitudinal data related to activity levels, heart rate variability, sleep cycles, and daily routines. When integrated with advanced analytics, these data streams enable the development of predictive systems capable of identifying early warning signs of insomnia before chronic symptoms develop. Such proactive monitoring approaches can transform sleep health management from a reactive clinical intervention to a preventive healthcare strategy.

Despite these advancements, several limitations remain within the current research landscape. Many studies rely on relatively small datasets or controlled laboratory environments, which limits the generalizability of predictive models. Furthermore, there is a noticeable lack of standardized datasets

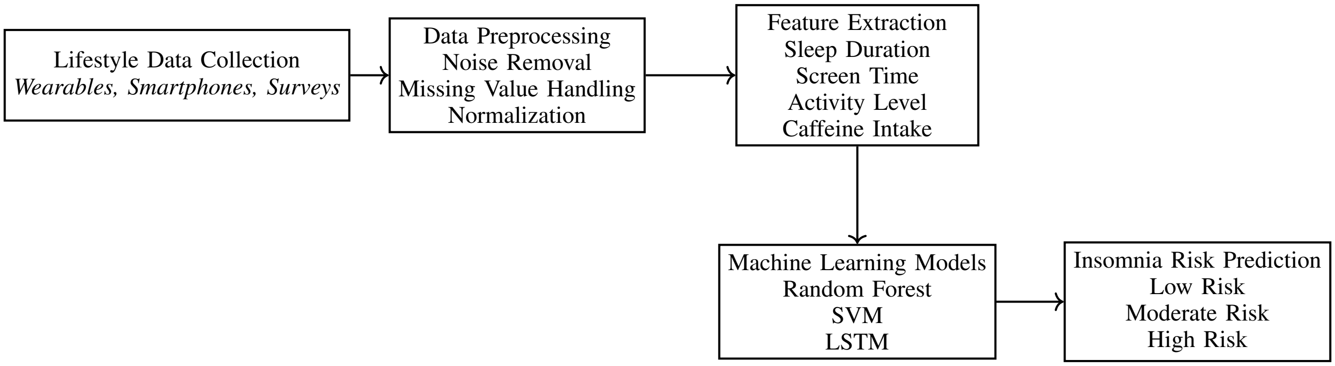

Fig. 15: Graphical abstract illustrating the proposed lifestyle-driven insomnia prediction framework integrating behavioral data collection, preprocessing, feature engineering, and machine learning-based risk forecasting.

that integrate behavioral, physiological, and environmental factors in a unified framework. Another critical challenge involves the interpretability of machine learning models used in healthcare contexts. For clinical adoption, predictive systems must provide transparent explanations that allow healthcare professionals to understand the factors influencing insomnia risk predictions.

To address these challenges, this review proposed a conceptual predictive framework that integrates lifestyle monitoring with machine learning–based risk forecasting. The proposed framework combines multiple data sources—including wearable sensors, smartphone activity logs, and lifestyle surveys—to generate comprehensive behavioral profiles. These data are processed through preprocessing pipelines and feature extraction modules before being analyzed by predictive models capable of estimating insomnia risk levels as shown in Figure 15. Such an integrated approach has the potential to support early detection of sleep disorders and facilitate personalized sleep health recommendations.

Looking forward, future research should focus on developing personalized sleep recommendation systems that leverage continuous behavioral monitoring and adaptive machine learning algorithms. Advances in explainable artificial intelligence will also play an important role in enhancing trust and transparency in clinical decision support systems related to sleep health. Additionally, the integration of insomnia prediction models with digital healthcare ecosystems—including telemedicine platforms, remote patient monitoring systems, and AI-based health assistants—could enable real-time guidance for individuals experiencing sleep disturbances.

In conclusion, the findings of this review suggest that lifestyle behaviors represent a critical and modifiable determinant of insomnia. The integration of machine learning with lifestyle data analytics provides a promising pathway for developing intelligent systems capable of predicting insomnia risk and supporting preventive healthcare strategies. As digital health technologies continue to evolve, interdisciplinary research combining sleep science, behavioral analytics, and artificial intelligence will be essential for building scalable solutions that promote healthier sleep patterns and improve overall well-being.

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