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Review

Computational Approaches to PTSD in the Middle East

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Abstract

Posttraumatic stress disorder (PTSD) poses a major mental health threat in the Middle East, where people experience ongoing conflict, displacement, and trauma. This study summarizes the use of computational and data-driven approaches, including machine learning (ML), biomarker identification, network analysis, and factor analysis, to understand, diagnose, and treat PTSD in the Middle East. A detailed search of the Scopus database led to the inclusion of only relevant original/research studies that met strict inclusion criteria for human subjects, geographical focus, and use of computational approaches. Studies have suggested that computational models can predict PTSD onset, biomarkers from biology and neuroimaging, complex symptoms, and comorbidity networks. They enable the development of precision psychiatry and culturally adapted diagnostic measures for conflict-affected displaced population samples. The relevance of multimodal pre-trauma screening, as well as the importance of consistent biological markers (inflammation, gene expression), is underscored by a comparative analysis of predictive models (AUCs of 0.73-0.92). Nonetheless, the cross-cultural validity of PTSD symptoms and the presence of computer resources in the region remain concerning. This article describes the revolutionary potential of computational

psychiatry for improving mental health research and practice in the Middle East. It emphasizes the importance of culture-sensitive, scalable application with respect to resources.

Keywords
Posttraumatic stress disorder (PTSD); Middle East; computational psychiatry; machine learning; biomarker discovery; network analysis; precision mental health; conflict-affected populations; data-driven methods

1. Introduction

Posttraumatic stress disorder (PTSD) is exacerbated in the Middle East by ongoing war, displacement, and accumulated trauma of the population. The violence associated with the Iraq War and Syrian Civil War has inflicted high levels of psychological trauma, which can be inferred from the high rates of PTSD among affected individuals. Evidence shows that symptoms of PTSD are substantially higher in conflict-affected populations than in the general population, which is directly related to persistent threats and violence common to such settings [1-3]. In a previous study of Syrian refugees in Lebanon, more than 30% met the criteria for PTSD. This highlights the importance of providing mental health care in resource-poor settings [4]. As a result, displacement, which is often directly related to armed conflict, compounds psychological vulnerabilities; scholars have found that refugees face unique stressors that reflect the compounding of pre-migration trauma and resettlement challenges [5]. A review reported that the prevalence of PTSD in children and adolescents from conflict-affected areas, including Palestine and Iraq, ranges between 23% and 70% [6]. This requires mass efforts in treating the symptoms of PTSD and higher-level psychological issues related to violence and displacement in Iraqi populations in the Middle East [7].

PTSD may be studied in this way by utilizing computational psychiatry to develop machine learning (ML)/network analysis and biomarkers for the diagnosis, treatment, and understanding of PTSD. Indeed, data-driven methods on neuroimaging data (e.g., fMRI and neuroelectrical recordings) are starting to reveal good potential for classifying PTSD subtypes based on neural signatures [8, 9]. Such approaches can localize brain regions (e.g., the insula and amygdala) that predict PTSD, clarify sources of heterogeneity of symptoms in PTSD, and identify potential mechanisms through which treatment works [8, 9]. Simultaneously, there is an endeavor to identify biomarkers using multi-omics technologies (including genomics, transcriptomics, and metabolomics) so that biological markers can be used to diagnose disease, which would revolutionize both diagnosis and treatment [10-12]. Exhaustive study results expressed quantitative trait methylation loci and other biomarkers for PTSD risk/diagnosis; the biological basis of each disease was interpreted, which could set personalized therapy options [13, 14]. The study of computational models would also provide a global view of the psychopathological mechanisms responsible for PTSD and would allow the creation of more personalized therapeutic options [15, 16]. Together, these two advances provide perhaps the most powerful statement on how computational methods will determine the future of PTSD and precision psychiatry.

This review synthesizes recent studies applying computational tools—such as ML, biomarker discovery, and network analysis—to PTSD in Middle Eastern or conflict-affected populations. The

primary aims are to evaluate their utility for risk prediction, diagnosis, and treatment personalization, while examining their applicability in contexts shaped by ongoing conflict, displacement, and distinct cultural factors. Key challenges, including the cross-cultural validity of assessment tools and computational models, are explored throughout, with a focused discussion in Section 4.2.

2. Materials and Methods

We conducted a thorough literature search using the Scopus database to identify peer-reviewed studies that applied computational or data-driven methods to investigate PTSD, particularly among Middle Eastern populations or people directly affected by regional conflicts. The goal was to determine the kinds of approaches being used and how they might help understand trauma in these specific contexts. The research concentrated on three conceptual domains: geographic scope, disorder of interest, and analytical methodology. The area includes the Middle East, Iran, Saudi Arabia, Egypt, Jordan, Lebanon, Qatar, the United Arab Emirates, Turkey, Iraq, Palestine, Kuwait, the Gulf area, the Gulf Cooperation Council (GCC), and Afghanistan. The disorder domain used the terms PTSD, posttraumatic stress disorder, and posttraumatic stress. In the methodological domain, the terms mentioned encompass ML, artificial intelligence, deep learning, predictive models, biomarkers, data-driven, cluster analysis, algorithms, and computational methods.

This study was confined to original research articles published in English. Studies were included if they involved human participants diagnosed with, assessed for, or at risk of PTSD; if conducted on Middle Eastern populations or those directly affected by conflicts in the Middle East, such as veterans of Iraq or Afghanistan wars and refugees from Syria, Iraq, or Afghanistan; and if they employed computational, data-driven, or machine-learning methodologies as a core component of the analysis. Acceptable methodologies encompassed ML algorithms, such as random forest, support vector machines, and neural networks, in addition to clustering, network analysis, factor analysis, and other sophisticated statistical techniques for prediction or subtype identification. Only primary research publications were deemed appropriate for inclusion.

Studies were excluded if they concentrated on populations not associated with the Middle East or its conflict zones, lacked computational elements, depended exclusively on fundamental descriptive or inferential statistics, or investigated treatment efficacy without employing computational methods for prediction or biomarker identification.

The same rules were used to decide which articles to include and which ones to leave for both the first and second searches. As a result, this evaluation found and included relevant papers that met all of the standards. The characteristics and key findings of the studies are summarized in Table S1.

In addition to being data-driven, machine learning methods are not necessarily theory-driven. Still, network analysis and mediation models offer complementary insights by visualizing symptom relationships, the role of the central symptom, and possible causal pathways. Examples of these methods provide theoretical support that can be applied to feature selection, variable weighting, and clinical interpretation in ML models, particularly because of the multifactorial nature of PTSD's development, and the symptom network studies included (e.g., [17]) and mediation studies (e.g., [18]).

3. Computational Dissection of PTSD in the Middle East

3.1 Predicting PTSD Risk and Onset

There has been much excitement about computer models to predict when members of the military and other people who have experienced trauma will develop posttraumatic stress disorder. Such models typically use pre-deployment/post-trauma knowledge to identify at-risk individuals for targeted treatment and prevention. This section will review some important studies that have used ML and other computer-based techniques to predict who is at risk for developing PTSD, and when.

ML approaches are being increasingly applied to investigate different forms of pre-deployment data (psychological, cognitive, and biological) in relation to the prediction of post-deployment PTSD and symptom trajectories. Schultebraucks et al. also applied a prospective longitudinal approach in an independent sample of active-duty Army personnel, controlling for gene-environment positional interactions, and analyzed a combined data set comprising polygenic, epigenetic, metabolomic, and neuropsychological phenotypes. They also discovered that preservice factors such as the quality of sleep, anxiety, and cognitive flexibility are strongly associated with PTSD post-service [19]. Such predictions are accurate in the short-term prediction of PTSD diagnoses and symptoms over time, indicating promise for these models to be applied towards deployment readiness and risk prevention [19]. Papini et al. constructed an ML algorithm to predict an individual's risk of developing PTSD during military service. They studied a large sample of military service members, drawn from several pre-deployment reports. The predictive ability of the model's discrimination for each PTSD risk class suggests that it is plausible to predict almost all those who will develop PTSD before deployment, with a high rate of certainty [20].

In addition to PTSD, ML has been used to predict suicidal ideation in veterans and college students, but they mention only sex-specific predictors. Gradus et al. studied associations between deployment experiences of Iraq/Afghanistan war veterans and suicidal ideation (SI). They also found that certain traumas, such as sexual harassment, had a distinct relationship with suicidal thinking, especially in female veterans. The analysis applied classification tree and random forest techniques to normalize dense relationships among variables, with the potential usefulness of data-driven approaches for identifying at-risk groups [21]. Naghavi et al. followed this trend by constructing a model capable of predicting mental health outcomes, such as suicidal ideation, based on well-known psychological and demographic variables [22]. The importance of understanding how gender influences mental health outcomes is emphasized, as this knowledge could help shape more tailored interventions for at-risk populations [20]. In the following section, some computational approaches will be introduced for predicting PTSD and other psychiatric disorders. These models serve as examples of how such tools might be applied to guide prevention efforts and promote health among vulnerable groups. Multimodal data integration for PTSD risk prediction typically involves psychological, biological, and environmental inputs processed by machine learning models (Figure 1).

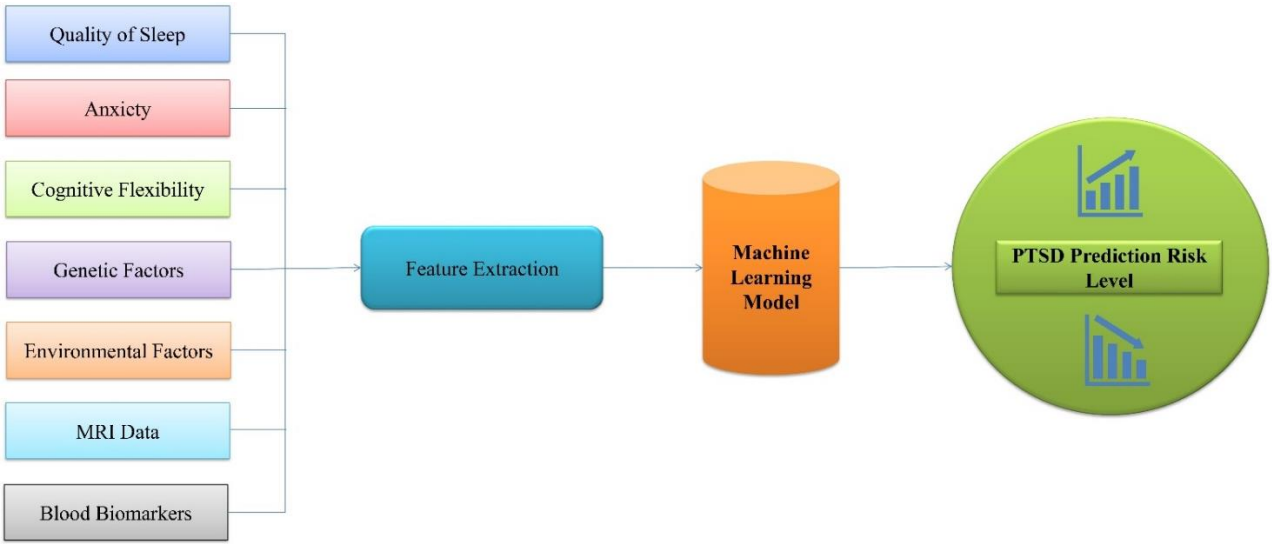

Figure 1 Conceptual framework of machine learning pipelines for predicting PTSD risk using multimodal data (e.g., psychological, biological, and neuroimaging inputs).

3.2 Diagnostic Classification and Biomarker Discovery

The diagnosis of posttraumatic stress disorder (PTSD) is dependent on reported symptoms and expert opinion. Recent advances in computational methodologies now allow the investigation of objective markers and diagnostic subtypes that might lead to increased precision, robustness, sensitivity, and specificity for PTSD diagnosis. In this subsection, we conduct a brief survey on computational diagnosis methods of current PTSD patients and the biological markers that have been associated with this disorder.

Recently, the application of blood-based biomarkers for objective PTSD diagnosis has become a main topic of research. Xu et al. investigated the discrimination of PTSD from HC and mTBI using routine clinical hematology blood assays [23]. The researchers found that some blood measurements could potentially be used as non-invasive diagnostic aids and suggested the incorporation of clinical laboratory data in PTSD screening strategies.

Siegel et al. built on this research by employing an integrated multi-omics (genomic, transcriptomic, and metabolomic; hereafter termed omics) approach to generate a repertoire of biological markers with predictive value as separators for cases (those with PTSD) and controls [24]. They reported that inclusion of candidate biomarkers, for example, inflammation and metabolism, increased diagnostic accuracy and thereby agreed for a more objective estimation of PTSD than with self-report/clinical evaluation alone. Tylee et al. revealed better insights into PTSD biomarkers and identified specific blood markers linked to the disorder. Their results highlighted the potential of blood-based biomarkers to complement current diagnostic methods and push individual risk profiling for PTSD [25]. Glatt et al. emphasized the importance of blood-based markers in PTSD diagnosis, particularly the relevance of inflammatory markers in symptomatology [26]. Their findings highlight the importance of conducting future research on the molecular pathobiology of PTSD and the possibility of an objective diagnostic tool using blood.

Recent advances in systems biology approaches have demonstrated the ability to combine high-dimensional molecular information with diagnostic algorithms to discover new biomarkers in the context of the disease. A representative example of integrating RNA-Seq biomarkers with

algorithmic approaches to predict complex clinical outcomes is illustrated in the liver transplantation context [27], and can be readily applied to PTSD research and is critical for risk prediction and subtyping.

Specific biological systems need to be examined further to explore the pathophysiology of PTSD. Yamin et al. examined the relevance of members of the acute phase proteins (C-reactive protein in particular, CRP) to PTSD in refugees and military personnel. They identified higher CRP levels in individuals with PTSD, thereby implicating inflammation as a major factor contributing to the etiology and persistence of this disorder. Arnetz et al. analyzed PTSD and neuroplasticity-related markers such as brain-derived neurotrophic factor (BDNF) and nerve growth factor (NGF) [28]. Changes in neuroplasticity markers could elucidate the characteristics of PTSD and offer clues to understand its pathophysiology. Nkiliza et al. identified oxidative stress as a priority target of neurobiological studies, particularly in the biomarker field and for helping to elucidate disorder etiology because of a clear role of oxidative stress with PTSD and involvement of lipid metabolites [29]. These findings suggest that some lipid metabolites may act as candidate biomarkers for PTSD, and clarification of more metabolic pathways is needed in PTSD. Hu et al. studied the mtDNA to evaluate its potential use as a biomarker of PTSD [30]. This led us to hypothesize that mtDNA mutations could be associated with PTSD, thus presenting a new strategy for identifying biomarkers of TRDs.

Magnetic resonance imaging (MRI), and fMRI in particular, has been used to distinguish PTSD from self-reported stress among veterans. Goel et al. also used a machine-learning approach along with fMRI to further specify self-report stress reactivity in veterans with PTSD [31]. It looks like ML can handle complex neuroimaging data fairly well. It even seems able to predict stress levels in individual patients with PTSD. This could make it a useful tool for real-time assessment, at least in practice. The paper also points out that combining neuroimaging with classification approaches seems to clarify diagnose. Using these methods together seems to support ways to help people diagnose and treat PTSD. These findings illustrate the growing potential of integrating computational approaches with biological and neuroimaging data to enhance diagnostic objectivity and precision.

3.3 Understanding Symptomology and Comorbidity through Network Analysis

Network analysis is beginning to show how PTSD symptoms overlap with each other and with other mental health problems. In this section, we examine studies that attempt to map out these connections, examine how symptoms co-occur, and how these patterns change over time or across groups. For example, Mohammadi et al. studied complex PTSD (C-PTSD) in an Iranian sample [17]. They wanted to determine which symptoms were central in the network. Some symptoms, such as worthlessness, did not fit perfectly, but most were tightly connected with other PTSD clusters. This suggests that a few core symptoms explain much of the shared distress in C-PTSD. They also used graphical models to show how the symptoms relate to each other. Some may act as pathways or mediators for other aspects of the disorder. This suggests that focusing on core symptoms could make treatment more effective. Recent network analyses also have further clarified symptom structure for various types of trauma [32] and for veterans [33], supporting the importance of some symptoms (e.g., negative alterations in cognition/mood) and symptom patterns (e.g., suicidal ideation).

Mediator analyses can also help show how PTSD is linked to anxiety and depression. This becomes tricky after major traumatic events. Barathie and Karam noted that PTSD symptoms often co-occur with depression and anxiety in a tangled mix of distress [18]. They found that certain PTSD symptoms, such as hyperarousal and avoidance, and depressive symptoms, such as anhedonia and excessive worrying, could predict general trends. In practice, this helps explain why PTSD often comes with sadness or anxiety, which can make recovery more difficult. The different groups showed different symptom patterns. Farhood et al. examined sex differences and found that girls reported higher distress than boys across symptoms, such as re-experiencing, avoidance, and mood/cognition. Some symptoms are more central in women than in men [34]. Bal and Jensen studied kids and found they often show different patterns than adults, with behaviors like irritability and separation anxiety standing out [35]. This shows why age and sex matter when assessing symptoms and planning treatment. Mediation analyses are used to examine the directionality of causal pathways (e.g., hypervigilance to anxiety in Lebanese samples), whereas network approaches model the interconnections among symptoms without assuming directionality. Both complement each other in elucidating PTSD comorbidity and heterogeneity.

Overall, network analysis is useful for determining how PTSD symptoms relate to each other and other mental health problems. It also shows how demographics can guide treatment. Understanding overlapping symptoms in this way gives researchers and clinicians more opportunities to design therapies that really fit individual needs, whether for PTSD alone or with other disorders. Network and factor analyses highlight interconnections among core PTSD symptom clusters, including intrusion, avoidance, hyperarousal, and negative mood (Figure 2).

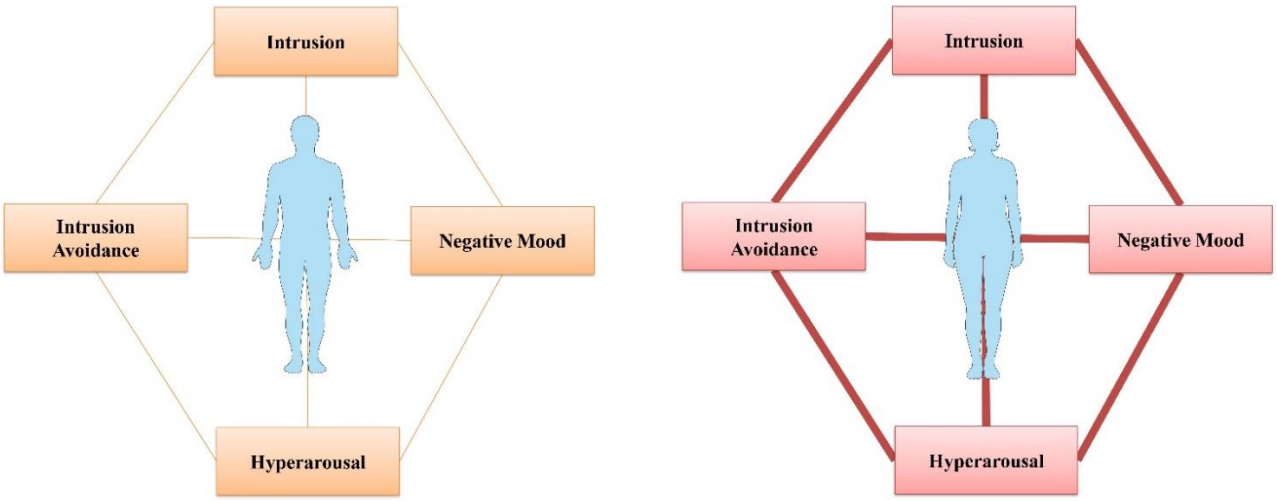

Figure 2 Core symptom clusters in PTSD, illustrating interconnections commonly explored through network and factor analysis in conflict-affected populations.

3.4 Validation and Application of Assessment Tools

Validating PTSD screening instruments in Middle Eastern contexts is essential for accurate identification. The PTSD Checklist for DSM-5 (PCL-5) has undergone preliminary adaptation in regional samples. Ibrahim et al. [36] translated the PCL-5 into Arabic and Kurdish dialects and tested it among 206 internally displaced Iraqis (Kurdish and Arab groups). The instrument showed good internal consistency (Cronbach's $\alpha = 0.85$), with an optimal cutoff score of 23 yielding 82% sensitivity

and 70% specificity. Barathie and Karam [18] conducted exploratory factor analysis of the PCL-5 in Lebanese individuals exposed to collective trauma, identifying a two-factor model and notable overlap with depression and anxiety symptoms. These findings represent initial steps toward context-appropriate assessment. Broader issues of cross-cultural validity, including symptom expression and tool adaptation, are discussed in Section 4.2.

The term posttraumatic growth (PTG) describes positive psychological development after trauma as proposed by Tedeschi and Calhoun [37, 38] and developed in theoretical and empirical studies [39]. There are several studies that demonstrate co-occurrence of severe PTSD symptoms and PTG in Middle Eastern refugees and conflict-affected groups [40, 41].

3.5 Comparative Insights and Most Promising Directions

A few of the studies reviewed in this report used machine learning (ML), predictive modeling, and related computational methods to predict PTSD risk, classify subtypes, locate biomarkers, or map the networks of symptoms. The performance measures, predictors, and validation of the most relevant papers are summarized in Table S2.

The predictive performance varied from moderate (AUC 0.73 in blood-based models) to excellent (AUC 0.90-0.92 in ensemble/tree-based models for suicidal ideation and PTSD risk). Multimodal models that combined psychometric, neurocognitive, and biological data generally performed better than single-domain models; for instance, Schultebraucks et al. obtained AUC 0.88 [19] with their multimodal approach, compared with 0.73 [23] with routine blood test-based models. The classification models (RF, SVM, GBM) showed AUC of 0.73-0.92; the regression/SEM accounted for 38-77% variance for the outcomes of the study (PTSD or posttraumatic growth).

The highest AUCs for risk prediction and subtyping were obtained for military and veteran cohorts (large N > 2000 in several studies). Predictive ML models were weak at representing refugee and IDP populations; there was a greater focus on regression or subgroup identification. Gender specific patterns were found, with sexual harassment significantly related to PTSD and depression in women [21]. Biological predictors (CRP, glucose metabolism, methylation/microRNA, gene transcripts) were often used in combination with psychometric measures (depression, anxiety, sleep quality). The studies reviewed section displays some recurring trends and positive results in computational studies. A combination of psychometric measures (anxiety, depression, sleep quality) and limited biomarkers consistently allows for effective risk stratification and early identification of high-risk individuals in pre-deployment screening [19, 20]. Multimodal integration of psychological, neuro-cognitive, and biological data results in a significantly higher predictive accuracy than single-domain models, as evidenced by increased AUC values up to 0.88 vs. 0.73 in blood-test-only models [19, 23]. A series of objective markers is consistently identified, including inflammatory markers (CRP, WBC), metabolic markers (glucose, HbA1c), and gene expression markers (e.g., GSTM1/GSTM2). These models have been successful in identifying at-risk individuals in military and student populations using ensemble and tree-based approaches (AUC 0.90-0.92) and are therefore considered useful [21, 22]. Gender-specific models suggest a different risk profile, especially for women, where sexual trauma has a higher risk [21]. Biological indicators of future risk—markers of allostatic load (cortisol, BDNF, lactate)—are examples of subthreshold biological alterations that provide early “infra-clinical” indicators of future risk [19, 42]. Lastly, central symptoms in Complex

PTSD networks, such as worthlessness and failure, are cross-cultural and are high priority targets for intervention [17].

In order to support future model design and variable weighting (especially given PTSD's heterogeneous etiology), important predictors and example levels from these studies are included in a new column in Table S1.

3.6 Special Populations and Unique Contexts

Before we can even get to treatment, we need to understand what mental health issues are going on in traumatized communities in the Middle East. It is not just about refugees — though a lot of German studies focus on trauma experiences and PTSD rates. People with comorbidities of mental health issues also matter. Honestly, how these people view mental health services is part of the story. Recently, researchers have examined Iraqi and Syrian refugees and even Palestinians. The question is whether PTSD overlaps across these groups. Yamin et al. studied Middle Eastern refugees connected to the U.S. [28]. They focused on trauma before displacement and differences in mental health responses. Finally, they found that most immigrants had severe PTSD symptoms. At the same time, many have also described posttraumatic growth (PTG). Positive changes in life and coping after trauma. Therefore, trauma and growth often exist together, which is interesting.

Arnetz et al. looked at neuroplasticity and PTSD symptoms in refugees dealing with mental health issues [1]. Their results suggested that molecular factors might help explain why some people react differently. This could guide personalized approaches to support PTG. They also stressed that treatment should address both distress and growth, not just one. Ghafouri et al. explored mothers in a diaspora. The Peace and War Moms study showed that PTSD and PTG are connected in complicated ways. Many mothers showed remarkable resilience, often stepping into a protective role after trauma. They also found four clusters of PTSD and PTG levels. That is important — it shows that interventions need to be tailored to each group and their resources. One size does not fit all. Overall, these studies suggest that understanding trauma and growth together while keeping culture, context, and individual differences in mind is key for mental health interventions. It's messy, yes. Complicated, yes. However, that is how things really work in practice. The distress of comorbid sufferers differs from those with just one or the other mental disorder or epilepsy alone. Salmanipour et al. studied neuropsychological development in individuals with complex PTSD (C-PTSD) and epilepsy as examples of psychosocial factors. They found that this could be measured as a function of ego strength or self-concept [43].

PTSD in the Middle East is often postponed and avoided because of cultural attitudes. Cultural beliefs were found to be important predictors of intention and utilization of mental health services [44], and common stigmatizing stereotypes about mental illness were reported in a Turkish national sample [45]. These cultural factors reinforce other cross-cultural validity concerns discussed in Section 4.2 and underscore the need for evidence-based culturally specific prevention and intervention practices.

The authors reported in a follow-up investigation that both self-concept and ego strength were moderators of the relationship between posttraumatic symptomology and PTG. These results indicated that a positive self-image is linked to positive posttraumatic growth and that, therefore, treatment may be helpful if patients can be assisted to develop a strong sense of self.

4. Discussion

This review examines the use of analytical frameworks in PTSD, particularly among military personnel and veterans, as well as their possible application in a Middle Eastern context. The following papers highlight the growing importance of ML and other sophisticated statistical techniques for understanding, predicting, and ideally treating PTSD and related psychiatric conditions.

4.1 The Feasibility of Precision PTSD Care in the Middle East

The data from relevant papers support the fact that precise PTSD treatment can be performed using computer-based models for risk stratification and personalized diagnosis. ML models have shown significant success in the prediction of post-deployment PTSD risk based on predeployment self-reported data. One study developed an ML model targeting US Army personnel using records that successfully classified PTSD 2-9 months after deployment and was generalizable across disparate time periods and geographic distributions. This signature, based on only 58 basic parameters, achieved a performance comparable to signatures that require a much broader set of predictors, supporting this model as an efficient and robust tool for risk stratification [20]. Diagnosing those at higher risk before deployment allows for tailored preventive and early intervention programs [20].

In addition to the prediction of risk, computational approaches allow personalized diagnosis by recognizing particular subtypes of PTSD. In an RF analysis-aggregated clustering study that considered clusters as a means, related to k-means techniques for their tree, from which two PTSD types, S1 and S2, were derived, both in veterans (subtypes, with clinically assigned reporting of CAPS in terms of DSM-IV). On all scale items, patients in subtype S2 showed more severe symptoms than those in S1 and healthy controls [24]. This subtyping enables a more nuanced appreciation of PTSD symptoms, beyond the single diagnostic category, to potentially inform individualized interventions.

The use of ML for classifying self-reported stress responses in combat-related PTSD veterans from fMRI data can also be noted.

The potential of this technology, based on an anisotropic blurring algorithm for the interpretation of high-dimensional fMRI data, has been previously demonstrated when considering potential clinical applications such as real-time therapeutic interventions. The best-performing ML model predicted stress responses with a very low RMSE, indicating that personalized, objective assessment of an individual's internal brain state related to stress is feasible using external fMRI data [31].

Complicated models are useful for determining when to start and defer treatment. Background Factors in electronic health records (EHR) associated with depression treatment initiation and time to therapy were studied among veterans using ML and regression models to predict treatment initiation. This demonstrates how computational approaches can be used to pinpoint barriers to mental health treatment and help increase the uptake of mental health services [44]. Similar statistical approaches to the one proposed in this study could be applied to a pre-deployment population to identify groups with higher scores of pathological metrics (such as PCLs - PTSD Checklist, HAD-A - Hospital Anxiety and Depression Scale/Anxiety, and HAD-D/SI: Hospital Anxiety and Depression Scale was used for depression) early detected before deployment [42]. The many uses underscore the great applicability of computational methods in the precision treatment of mental health.

4.2 Cross-Cultural Validity of PTSD Constructs

The majority of reviewed studies rely on data from Western military and veteran cohorts, primarily from the United States and France [20, 21, 24, 42]. Although these provide robust computational insights, they do not address the cross-cultural validity of PTSD constructs or assessment instruments in Middle Eastern contexts. Commonly used tools—such as the PTSD Checklist (PCL-5), Hospital Anxiety and Depression Scale (HAD-A/D), and Clinician-Administered PTSD Scale (CAPS)—were developed and validated predominantly in Western clinical settings.

In Middle Eastern populations, trauma frequently involves collective experiences, prolonged displacement, and ongoing conflict, leading to distinct symptom expressions. Symptoms may manifest somatically, through cultural idioms of distress, or via heightened stigma, which standard Western criteria may not fully capture. Preliminary validation efforts highlight these challenges: Ibrahim et al. [36] adapted the PCL-5 for displaced Iraqi populations, achieving good reliability (Cronbach's $\alpha = 0.85$) and establishing a cutoff of 23, while Barathie and Karam [18] identified a two-factor structure in Lebanese samples with substantial overlap between PTSD, depression, and anxiety symptoms. Cultural barriers further complicate assessment and help-seeking; Panaite et al. [44] and Sönmez and Karaoğlu [45] demonstrated that stigmatizing attitudes and cultural beliefs significantly influence mental health service utilization in Middle Eastern and Turkish samples.

The limited discussion of cross-cultural validity in the current literature represents a critical gap. Computational models depend on valid, culturally relevant input data and constructs. Future research applying these methodologies to Middle Eastern populations must systematically evaluate existing instruments and develop culturally tailored measures to ensure accurate risk stratification, subtype identification, and personalized treatment.

4.3 Biomarker Consistency and Promise

The resources included are evidence of increasing interest among audiences in learning about and predicting PTSD by using biological markers and the success of many who have done so. These biomarkers add objective value to support self-reports and clinical assessments.

Gene expression in the blood is a key area for research. Blood-based gene expression markers of PTSD risk and resilience among deployed Marines. This is consistent with the notion that gene expression in peripheral blood, particularly by immune-system genes at the pre-trauma baseline, would differ between Marine trauma-exposed participants who did and did not later develop PTSD. The study aimed to provide a predictive Biomarker Panel for Incipient PTSD in those at high risk of developing the disorder using gene expression [26]. This relays the power of genetic markers for predicting sensitivity prior to stress exposure.

The promise of biomarker-driven approaches is echoed by complementary in silico and computational studies. A computational docking study was applied to explore the interaction between monoamine oxidase-A and zingerone and its related structures [46], in the quest to realize potential neuroprotective mechanisms that would impact the pathophysiology of PTSD. Complementary in silico studies from other areas demonstrate the usefulness of systems biology to study complex biological pathways. A model of the anti-inflammatory and cytoprotective properties of a compound over multiple targets, for example in oncology [27], has been developed that could be adapted to uncover the inflammatory and neuroprotective processes involved in the pathophysiology of PTSD. These examples of methodology spanning disciplines demonstrate the

potential of molecular modeling and empirical biomarker data to advance discovery in precision psychiatry. The studies demonstrate the importance of combining machine learning and molecular modeling approaches with valid empirical biomarkers to improve predictive accuracy and precision psychiatry in resource-limited environments.

A second study supported the relevance of biological markers by exploring ML applications in distinguishing PTSD subtypes and associated biology. In this study, the potential of blood biomarkers to discriminate between the established clinical subtypes of PTSD (S1 vs. S2) was examined in veterans with 6-10 years of posttraumatic experience [24]. This represents a step forward in understanding the molecular underpinnings of different PTSD phenotypes, with potential implications for tailored biological therapeutics.

The potential to screen for PTSD and Traumatic Brain Injury (TBI) in veterans by measuring regular clinical laboratory blood tests is also considered [20]. This indicates that easily obtainable and minimally invasive biological measures can be integrated into screening protocols, thereby enhancing the accessibility of biomarker-based evaluations.

A particular ML model for forecasting post-deployment PTSD risk predominantly utilized self-reported data; however, the authors noted that some of the most efficacious models, sourced from other military personnel samples, incorporated "biomarkers and neurocognitive predictors" alongside self-report data [20]. This indirectly substantiates the enhanced utility and resilience that biological markers may confer on predictive algorithms.

Neuroimaging techniques function as biological correlates of blood-based markers. A feasibility study illustrated an ML methodology to categorize self-reported stress responses obtained from multisession functional MRI (fMRI) data in veterans with combat-related PTSD. This technique, which analyzes fMRI data from gray matter, yielded favorable results for categorizing intrinsic brain states into eight significant classes. This indicates that fMRI could serve as a potent neurobiological biomarker for real-time evaluation and management of stress [31].

These findings collectively highlight the potential of various biomarkers, such as gene expression, standard blood tests, and neuroimaging, in improving the accuracy of PTSD diagnosis, risk assessment, and subtype classification. The uniformity observed across studies on these biological parameters attests to the necessity of their inclusion in computational models aimed at improving the accuracy and specificity of PTSD treatment.

4.4 Clinical and Humanitarian Implications

The use of computer-assisted screening and assessment in clinical practice or during humanitarian action may have high potential to enable early intervention and effective deployment of resources, for example in the Middle East, where mental healthcare treatment capacity is currently limited. This approach of measuring PTG alongside PTSD symptoms aligns with the PTG assessment perspective in PTG frameworks, which is a balanced approach that focuses on resilience [37-39].

An important treatment outcome would be the ability to risk-stratify pre-deployment, or pre-trauma exposure, the likelihood of PTSD. An artificial intelligence system that relies on pre-deployment self-reported data to predict in which cases the risk of PTSD after deployment is elevated might be able to identify people at a higher risk. Pre-deployment stratification of PTSD risk is possible and could improve the development of targeted prevention and early intervention

protocols [20]. This could be used in humanitarian emergencies to identify vulnerable populations or individuals before or soon after experiencing widespread trauma so that prophylactic mental health interventions can be provided.

ML has outlined different types of PTSD, such as subtypes S1 and S2, which represent separate symptom profiles [24]. Personalized medicine is a term that is really what is aimed for. Instead of treating everyone with PTSD in the same way, doctors can look at each person's symptoms and their severity. This kind of detail might improve treatment and help use therapy resources more wisely.

ML can help a lot here. You can monitor mental health in real time. For instance, self-reported stress from fMRI presents an especially attractive possibility for future clinical applications and possible instant therapeutic deployment [31]. Essentially, you could track reactions, tweak treatments as you go, or even provide patients with immediate feedback.

From a humanitarian perspective, computation can also address access issues. Some veterans delay or never start receiving depressive care. Current models may help to explain why [44]. Tools could flag the highest-risk people, target resources, adjust interventions, and steer corrective action where needed.

ML has also looked at gender-specific links — trauma, psychopathology, and suicidal thoughts — in veterans. The next generation of precision-based treatments may be coming soon [21]. Knowing these risk factors could help in designing preventive interventions that fit different groups.

Ultimately, computational tools could make mental healthcare more proactive, individualized, and efficient. They might help identify risks early, personalize diagnoses, monitor patients in real time, and use resources better. Such subtyping supports personalized treatment approaches, optimizing resource allocation. Ultimately, computational tools have the potential to transform mental healthcare into a more proactive, individualized, and efficient system. Computational tools may also be used to identify subclinical PTSD (those who have clinically relevant symptoms that do not meet criteria for PTSD), so that earlier preventive interventions may be implemented in high-risk populations in conflict-affected areas.

4.5 Limitations and Future Directions

Related studies underscore notable progress in computational methodologies for PTSD; however, distinct limitations and unique avenues for future investigation are evident. A notable constraint of numerous studies is the sample size, especially for specific high-risk populations. For example, in a study of pathological scales, there were very few participants in several high-score categories (e.g., n = 1 or n = 2) [42]. A study that categorized PTSD subtypes utilized a discovery sample comprising 74 patients with PTSD and 71 healthy controls, alongside a validation sample of 26 PTSD cases and 36 healthy controls [24]. Small sample sizes may limit the generalizability and statistical power of the findings, underscoring the need for larger, longitudinal studies to ensure robust, replicable results.

A vital component of future research is the replication of results across various populations and methodologies. Although a single study illustrated the effective temporal and geographic generalization of their ML model for PTSD prediction through testing on a separate dataset [20], such stringent validation has not been applied consistently. Comparing the AUC of their model with those that use biomarkers and neurocognitive predictors shows that models that use only self-reports may not fully capture the complexity of PTSD risk [20]. This suggests a potential strategy for

incorporating multiple data sources, including self-reports, clinical assessments, neuropsychological measures, and biological features, to build more complete and accurate predictive models.

High-dimensional data such as whole-brain cortical fMRI data face many technical challenges that are difficult to address. As noted, this information is "too high dimensional to support efficient ML training and requires some form of feature reduction" [31]. More studies are needed to study and improve the effective handling of data/feature reduction algorithms to make these advanced neuroimaging techniques more feasible for clinical use.

A key limitation is the predominant focus on Western military cohorts across the included studies. As detailed in Section 4.2, this restricts generalizability to Middle Eastern contexts, where trauma presentation and cultural factors differ markedly. Future investigations should prioritize culturally appropriate measures and validation in diverse regional samples.

It is crucial to keep the tools cheap and portable, so they can be taken into the field, where such computational tools can have a big impact on clinical practice and humanitarian relief, particularly in places with limited resources. fMRI provides detailed data, but getting there is not easy. Further research must investigate the translation of outcomes from complex models into simpler and more accessible screening and monitoring methodologies suitable for various field conditions. This may encompass the use of routine clinical laboratory blood tests [20] or the future development of mobile applications for self-reporting and basic cognitive assessments guided by advanced ML insights. The focus should be on developing practical solutions that bridge cutting-edge research and real-world practice.

Lastly, the increasing use of computation-based approaches that combine transcriptomic markers with diagnostic algorithms in biomedical research in general will serve as an example of the wider application of such data-driven precision medicine approaches and as a potential methodological model for future computational health research [13, 47].

5. Conclusions

This study emphasizes the increasing potential of computational methods to transform PTSD research and therapeutic approaches in the Middle East. Researchers have employed ML, network analysis, and biomarker identification to elucidate the molecular and psychological intricacies of PTSD in communities affected by violence. These data-driven methods have the potential to improve mental health care by facilitating early risk identification, patient stratification, and personalized diagnostic approaches. The field remains constrained by limited regional data and challenges in cultural adaptation (see Section 4.2), and disparities in computational resources.

Future research should focus on creating culturally sensitive models, integrating multimodal data, and fostering collaborations that align global computational psychiatry with the needs of the Middle Eastern population. Computational methods have the potential to enhance diagnostic, therapeutic, and resilience outcomes for individuals affected by trauma throughout the region.

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Author Contributions

EA carried out the gathering and analyzing of studies. BS participated in the design of the study and drafted the manuscript. EA and BS conceived of the study and participated in its design and coordination as well as the analyses of data. All authors read and approved the final manuscript.

Competing Interests

The authors have declared that no competing interests exist.

AI-Assisted Technologies Statement

During the preparation of this work the authors used Grammarly and ProWritingAid in order to check spelling and grammar. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the content of the manuscript.

Additional Materials

The following additional materials are uploaded at the page of this paper.

1. Table S1: Characteristics and key findings of the studies on computational approaches to PTSD in Middle Eastern or conflict-affected populations.
2. Table S2: The table below summarizes the predictive performance and key predictors, resulting from the computational studies.

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