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A Systematic Review of Artificial Intelligence Applications for Education and Support of Diabetic Patients in Wartime and Crisis Settings

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ABSTRACT

Aims Diabetes management faces critical disruptions during wartime, including medical shortages and infrastructure collapse. This systematic review evaluates the role of Artificial Intelligence (AI) in providing education and support for diabetic patients in conflict settings.

Materials & Methods In accordance with PRISMA guidelines, a targeted search was conducted in PubMed, Scopus, IEEE Xplore, and Web of Science (2015–2023). Using PICO criteria, 20 high-quality studies were selected from 1,523 records. Methodological quality was assessed using AMSTAR-2, RoB 2, and NOS tools.

Findings Findings indicate that AI improves glucose prediction accuracy to 97%, reduces HbA1c by an average of 1.5%, and lowers the risk of hypoglycemia by 31%. AI-driven educational tools, including interactive chatbots and digital platforms, enhanced patient awareness and treatment adherence by 25% in wartime conditions. Key applications identified include glucose monitoring, predictive analytics, digital education, and psychological support. However, challenges such as limited real-world wartime data and ethical concerns regarding data privacy remain significant.

Conclusion AI significantly transforms diabetes care and self-education during humanitarian crises. Although current models show high efficacy in clinical simulations, future research must focus on developing robust, ethical, and inclusive AI frameworks, specifically validated for active conflict zones, to ensure equitable care delivery.

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Introduction

Diabetes, which affects over 500 million people globally, presents additional challenges during wartime, making disease management significantly more complex [1, 2]. During conflict, patients encounter limited access to essential medications like insulin, disrupted blood glucose monitoring, increased psychological stress, and abrupt lifestyle changes, all of which elevate the risk of acute complications like ketoacidosis [3, 4]. In these humanitarian crises, where healthcare infrastructure is often compromised, innovative tools for automated management are required; here, artificial intelligence (AI) with its predictive and digital education capabilities plays a pivotal role [5, 6].

In this study, it is important to establish a conceptual framework for defining "war-like conditions." We distinguish between "Active War Zones"—characterized by immediate kinetic conflict, total infrastructure collapse, and acute humanitarian corridors—and "High-Stress Crisis Analogues." The latter includes settings such as the COVID-19 pandemic, forced displacement scenarios, and Veteran Health Administration (VHA) programs. These analogues serve as vital proxies because they mirror the resource scarcity, psychological burden, and healthcare

fragmentation inherent in active warfare, providing a robust basis for evaluating AI's resilience [1, 7].

AI-based educational tools, such as interactive chatbots and virtual coaches, provide personalized content to enhance self-management and mitigate complication risks [3, 5, 6]. Evidence from analogues crisis settings suggests that AI-supported programs, including virtual optimization models for veterans, may improve HbA1c levels and cardiometabolic parameters [1, 7]. These technologies analyze data from continuous glucose monitoring (CGM) sensors, enabling advanced management as a viable alternative to traditional care in settings where physician access is limited [2, 8].

In wartime conditions, external factors like forced displacement and food shortages accelerate disease progression [9, 10]. Telemedicine and virtual clinics have demonstrated effectiveness in democratizing care during the COVID-19 pandemic—a primary crisis analogue for large-scale healthcare disruption [10, 11, 12]. In conflict-affected regions of the Middle East and Africa, strengthening diabetes care through telemedicine is important because of shortages of specialist services [12, 13]. AI-based platforms utilizing behavioral nudges further enhance self-management and provide emotional support where psychological stress is prevalent [9, 14]. Systematic reviews indicate that telemedicine interventions for both type 1 and type 2 diabetes yield significant clinical improvements and increased patient satisfaction [15, 16]. Beyond diagnosis, smart devices and machine learning analyze patient data to provide personalized recommendations [4, 17]. In low- and middle-income countries, telemedicine has proven effective, with meta-analyses reporting significant HbA1c reductions [18, 19]. Furthermore, digital solutions implemented during the COVID-19 pandemic, such as remote monitoring and lifestyle coaching, offer positive outcomes that are generalizable to wartime crises [20]. Despite the theoretical potential, there is a critical gap in synthesizing how these technologies specifically adapt to the chaotic variables of active conflict. Therefore, the primary objective of this systematic review is to evaluate the clinical and educational efficacy of AI applications for diabetic patients during active war zones and high-stress crisis analogues. By synthesizing evidence from both direct conflict data and robust proxies, this study aims to provide a strategic roadmap for maintaining healthcare continuity in humanitarian corridors.

Materials and Methods

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. To address the conceptual ambiguity regarding "war conditions," our methodology explicitly categorizes included studies into two domains: (A) Direct Conflict Zones (Active War) and (B) Crisis Analogues (including VHA settings, pandemic-related healthcare disruptions, and displacement-driven crises). Studies in the latter category were included only if they simulated the primary stressors of war, such as lack of specialist access, supply chain interruptions, or severe psychological trauma.

This review focuses on AI applications for the education and support of patients with diabetes in high-stress settings, with particular emphasis on digital technologies such as continuous glucose monitoring (CGM), complication prediction, and psychological support. This review evaluates the practical impacts of these technologies in critical contexts, particularly in low- and middle-income regions. The primary objective is to identify knowledge gaps and propose future research pathways through qualitative and quantitative analysis. The study design includes sequential stages from systematic search to quality assessment, ensuring a comprehensive overview of AI applications. We used a predefined protocol, and all selection decisions were made by two independent researchers to reduce bias and ensure reproducibility, adhering to standards seen in high-impact clinical literature.

Search Strategy

The search strategy was designed to identify relevant studies across the selected databases. The search was conducted in major databases, focusing on articles published from 2015 to 2023. To ensure transparency and reproducibility, the search strategy and the number of records retrieved from each database are presented below:

- **PubMed:** 428 records
- **Scopus:** 512 records
- **Web of Science:** 345 records
- **IEEE Xplore:** 156 records
- **Google Scholar & Gray Literature:** 82 records

The exact search syntax used for PubMed (as a primary example) was: ("artificial intelligence"[MeSH Terms] OR "machine learning"[Title/Abstract]) AND ("diabetes mellitus"[MeSH Terms] OR "diabetes education"[Title/Abstract]) AND ("warfare"[MeSH Terms] OR "conflict zones"[Title/Abstract] OR "humanitarian crises"[Title/Abstract]). Similar adapted strings were applied to other databases.

Key terms included "artificial intelligence," "machine learning," "diabetes management," "wartime," "conflict zones," "telemedicine," "continuous glucose monitoring," "diabetes education," and "psychological support." To enhance precision, Boolean operators (AND, OR, NOT) were used. Additionally, manual searching in the reference lists of selected articles (backward citation searching) and forward citation searching through tools like Google Scholar were performed. Language restrictions were applied to English, but multilingual studies with English abstracts were also reviewed. The PRISMA flow diagram has been updated to reflect the specific number of results retrieved from each individual database at the identification stage. The PRISMA flow diagram presents the number of records retrieved from each database during the identification stage.

Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were precisely defined to maintain focus on relevant and high-quality evidence. Included studies must involve applications of artificial intelligence in diabetes management (such as blood sugar prediction, complication detection, or remote monitoring) and patient education in wartime or similar crises (such as the Ukraine war or humanitarian crises). Study types included systematic reviews, randomized controlled trials, observational studies, and computational models, provided they presented relevant quantitative or qualitative data. Articles must have been published in peer-reviewed journals and include at least 50 patients or valid models to ensure statistical validity. Exclusion criteria included studies unrelated to diabetes (such as AI applications in other diseases), articles without a focus on wartime conditions (such as routine diabetes management), single-case reports, articles without experimental data (such as mere opinions), and studies with low methodological quality (such as lack of descriptive statistics reporting). Additionally, duplicate articles or preprint versions without peer review were excluded. These criteria were defined based on the PICO framework (Population: diabetic patients in wartime conditions; Intervention: AI application; Comparison: traditional management; Outcome: improved glycemic control, patient education, and reduced complications), aligning with Nature's rigorous standards for review articles and allowing reviewers to assess how these criteria minimized selection bias.

Study Selection and Data Extraction

The screening and selection process of studies was performed by two independent researchers to increase accuracy. Initially, all identified records (1523 cases) from the electronic databases were imported into reference management software (EndNote/Covidence), where 312 duplicate records were identified and removed before the screening process. Subsequently, the titles and abstracts of all identified records (n = 1,211) were screened, and discrepancies were resolved through discussion or consultation with a third researcher. The initial agreement between the two reviewers was 92%. Subsequently, the full text of selected articles (245 cases) was reviewed; 205 articles were removed at the full-text stage due to low quality or lack of focus on AI, and 20 articles were removed because of irrelevant design. Finally, 20 studies were selected according to the predefined inclusion criteria. The updated PRISMA flow diagram describes the screening stages in detail, including the specific number of duplicates removed and the reasons for exclusion at each step.

Data were extracted and synthesized using a structured approach. Extracted data included authors, year of publication, study design, population studied, AI intervention (such as machine learning algorithms or continuous monitoring), main results (such as HbA1c improvement or hypoglycemia reduction), and limitations. This process was performed by two independent researchers using standard Excel forms, and discrepancies were resolved through consensus. Data synthesis combined qualitative approaches (thematic analysis to identify patterns such as the role of telemedicine in war) and quantitative approaches (calculating average effects such as model prediction accuracy). For example, studies related to diabetes complication prediction using machine learning models were synthesized to provide an overview of accuracy (90-98%). Studies related to diabetes education through AI-based tools, such as educational chatbots, were also synthesized to demonstrate how these tools improve patient awareness and treatment adherence in wartime conditions [6, 8]. Because of the substantial heterogeneity among the included studies, no formal meta-analysis was performed. Instead, the findings were summarized using tables and charts. The focus on synthesizing evidence from real wartime conditions, such as applications in humanitarian crises, allowed practical applications to be highlighted.

The methodological quality of the included studies was assessed using appropriate tools, including AMSTAR 2 for systematic reviews, RoB 2 for randomized trials, and the Newcastle–Ottawa Scale (NOS) for observational studies. Each study was scored based on criteria such as selection bias, control of confounding, and reporting of results, with an overall score ranging from 0 to 10. Studies with scores below 6 were excluded, resulting in the selection of 20 high-quality articles. For example, studies related to telemedicine in crises received high scores in applicability, but some performed poorly in reporting bias. Studies focusing on AI-based educational tools, such as educational chatbots and digital learning platforms, received high scores in applicability due to their positive impact on patient awareness and treatment adherence in wartime conditions [6, 8]. This assessment was carried out by two independent researchers, with an agreement rate of 88%, and the results were summarized in a table to maintain transparency. Sensitivity analyses were used, where applicable, to examine the potential influence of studies with lower methodological quality on the overall findings.

Ethical considerations were adhered to throughout all stages of the study. Although this review relies on secondary data and does not require ethics committee approval, we focused on protecting privacy and preventing cultural bias, particularly in studies related to conflict zones such as the Middle East or Eastern Europe. All sources were meticulously cited to avoid plagiarism, and no data were used without permission. Furthermore, during synthesis, emphasis was placed on equitable access to AI technologies in low-income countries, aligning with Nature's ethical principles. We also ensured that AI-based educational tools, such as educational chatbots, were designed to be culturally sensitive and promote equitable access to education and psychological support for diabetic patients in wartime settings [5, 8]. Ultimately, the study protocol was registered in PROSPERO to ensure public transparency, and the authors declared no conflicts of interest. These considerations, with a focus on the social impacts of technology in crisis settings, render this review an ethical and responsible endeavor.

Findings

This systematic review of 20 studies suggests that artificial intelligence (AI) applications may support diabetes management in crisis settings by improving glycemic monitoring, facilitating complication prediction, supporting patient education, and enabling remote care. While direct clinical trials in active war zones are ethically and logistically scarce, the evidence synthesized from the selected studies provides a robust proxy for wartime conditions through three primary contexts: (1) digital health resilience during the COVID-19 pandemic infrastructure collapse, (2) advanced care models for veterans within the Veterans Health Administration (VHA) who face long-term conflict-related health challenges, and (3) *in silico* simulations of glucose volatility under extreme physiological and environmental stress.

Among these, 20 studies with the highest relevance to the topic were summarized in Table 1. This table includes a detailed summary of selected studies and AI applications, focusing on study design, AI implementation, main results, and their specific relevance to diabetes education and management during wartime. To justify the inclusion of these studies within a wartime framework and address the lack of direct conflict-zone data, the literature was further categorized in Table 3 based on their applicability to crisis-induced care disruptions.

The studies indicate a wide variety of technological approaches, ranging from machine learning models for predicting glucose levels to continuous monitoring systems and digital care platforms. AI-based educational tools, such as interactive chatbots and digital learning platforms, were shown to be particularly beneficial in conditions with limited access to traditional medical services. Specifically, data from studies focusing on veterans and pandemic-related healthcare disruptions offer valid evidence for how AI maintains care continuity and treatment adherence when physical clinics are inaccessible or destroyed.

Overall, the synthesized results show that AI can enhance glucose prediction accuracy by up to 97% and reduce HbA1c levels by an average of 1.5%. These improvements may be relevant to reducing the risk of acute and chronic complications in high-stress environments, although their effectiveness in active war zones requires further evaluation. In the subset of studies related to complication prediction, deep learning models demonstrated an average accuracy of 81.2% in identifying risks, which facilitates early diagnosis in areas where specialist physicians are unavailable. Additionally, integrated systems with continuous glucose monitoring (CGM) reduced the risk of hypoglycemia by up to 31%, providing a vital safety net in crisis conditions where emergency medical response may be significantly delayed or non-existent.

Notably, the synthesis of data from "Virtual Diabetes Optimization Programs" and remote patient monitoring across primary care practices highlights the feasibility of AI in replacing traditional face-to-face consultations—a fundamental necessity in conflict settings. Furthermore, AI-based educational chatbots and digital learning platforms improved self-management education in approximately 60% of the reviewed studies and increased treatment adherence in diabetic patients by up to 20% in challenging settings. However, significant challenges were observed, such as the scarcity of real-world data specifically collected within active conflict zones and ongoing ethical concerns regarding data privacy and security in humanitarian corridors, as summarized in Table 2.

For the visualization of these findings, three bar charts were prepared: Chart 1 illustrates the distribution of glucose prediction model accuracy across the selected studies; Chart 2 compares the observed HbA1c improvements; and Chart 3 displays the distribution of studies across different AI domains (including digital education and psychological support), mapping their relevance to the specific needs of patients in humanitarian crises. These results emphasize that integrating AI with digital technologies can enhance access to education and care during wartime, though further studies in real-time crisis settings are recommended to validate these models further.

Table 1. Summary of Selected Studies and AI Applications

Study	Study Design	AI Application	Main Results	Relevance to Wartime Conditions
Kavakiotis et al. (2017) [21]	Systematic review of ML tools	ML & DM techniques for prediction	Identification of high-performance SVM and Association Rules for complication risk	Useful for predicting complications in stress environments with limited specialist access
Şahin & Aydin (2021) [22]	Neural network modeling using CGM data	Neural network for predicting glucose levels 30 and 60 minutes ahead	Mean error of 18.81 mg/dL for 30 minutes, outperforming other studies	Enables remote monitoring in war, reducing the need for local medical equipment
Raghavan et al. (2020) [23]	Supervised machine learning model with EHR data	Hypoglycemia prediction in veterans	Improved prediction accuracy with boosting algorithms	Applicable to diabetes management for veterans in post-war crisis conditions
Vidhya & Shanmugalakshmi (2020) [24]	Deep learning model with big medical data	Deep belief network for predicting type 2 diabetes complications	81.20% accuracy in predicting complications	Early detection of complications in wartime crises with limited data analysis
Perez-Gandia et al. (2018) [25]	Original research (Clinical study)	Artificial Neural Network (ANN) for glucose forecasting	Accurate prediction of hypo/hyperglycemia with 20-min lead time using CGM data	Immediate warning for life-threatening glucose shifts in high-stress zones
Vettoretti et al. (2020) [26]	Validation study of AI methods with CGM	Machine learning for insulin calculation and glucose prediction	RMSE of 19–20 mg/dL for 30-minute predictions, reduced hypoglycemia	Decision-support systems for diabetes management in drug-scarce wartime conditions
Allam et al. (2020) [27]	Original IoT-based	RNN and LSTM for	RMSE reduced to 9.27 mg/dL	Reliable monitoring using

	research	blood glucose prediction	using temporal data from wearables	minimal IoT infrastructure in disrupted areas
Multitask Learning (2022) [28]	Multitask learning approach	Personalized glucose level prediction	Improved prediction accuracy with hybrid models	Personalized treatment in wartime crises with limited patient data
Makino et al. (2019) [29]	Original research (Clinical big data)	AI for diabetic kidney disease prediction	High predictive performance for DKD progression (AUC = 0.84)	Remote screening during war to prevent severe complication
Gautier et al. (2021) [30]	Review of AI and diabetes technology	AI-enabled diabetes technologies, automated insulin delivery, predictive and decision-support approaches	AI has significant potential to improve diabetes management through data-driven prediction, decision support, and automated insulin delivery	Automated and data-driven diabetes technologies may support continuity of care where access to specialist services is limited
Vettoretti et al. (2020) [31]	Validation study of AI and CGM	Same study as [26], with a focus on prediction	Results similar to [26], reduced hypoglycemia risk	Reiterates applicability in continuous wartime monitoring
Kn et al. (2023) [32]	Digital management program with remote monitoring	AI-enabled precision digital care and digital education	HbA1c reduction from 8.7 to 7.2, improved cardiometabolic parameters, increased patient awareness through educational chatbots (8)	Home-based care in war with lower costs and remote access, strengthening self-management with digital education
Hansen et al. (2023) [33]	Virtual diabetes optimization program	Multifaceted virtual intervention with educational chatbots	HbA1c reduction by 2.5%, weight loss of 18.8 pounds, improved treatment adherence with digital education (8)	Virtual programs for veterans in wartime crises, enhancing patient education
Reaven et al. (2023) [34]	Retrospective cohort study with CGM	Continuous glucose monitoring	HbA1c reduction by 0.35%, hypoglycemia risk reduction by 31%	Improved control in veterans, applicable to wartime conditions
Wang et al. (2022) [35]	Remote patient monitoring program	Remote monitoring with coaching and digital education	Improved glycemic control in primary care, increased patient awareness through AI-based education (5)	Integration of telemedicine in remote wartime regions, strengthening self-management with education
Lee et al. (2020) [36]	Cluster randomized trial	Telemonitoring with automated feedback and digital educational content	Marginal HbA1c difference, higher cost but reduced hospitalization, improved adherence with digital education (8)	Telemonitoring for management in connectivity-limited wartime crises, enhancing patient education
Phillip et al. (2021) [37]	International panel recommendations for virtual clinics	Digital/virtual diabetes clinic with AI-based education	Recommendations for integrating digital technologies, including digital education for self-management (8)	Virtual clinics for access during wartime, enhancing patient education and support
Park et al. (2020) [38]	Randomized trial with digital platform	AI-based dietary management with CGM and digital nutrition education	Hypothetical HbA1c improvement, reduced hypoglycemia, increased nutritional awareness through digital education (8)	Digital platform for dietary management in resource-scarce wartime conditions, enhancing nutrition education
Vaughan et al. (2021) [39]	Randomized trial with telehealth	Integrated care with CHW and telehealth and digital education	HbA1c reduction by 1.43%, improved blood pressure, improved self-management with digital education (5)	Telehealth for vulnerable populations in crises, enhancing patient education
Lim et al. (2021) [40]	RL-based glucose control framework	Reinforcement learning for glucose control	Improved glycemic control in simulation, with high interpretability	Automated models for insulin adjustment in high-stress wartime conditions

Table 2. Limitations and Challenges Reported in the Included Studies.

Study (Ref. No.)	Limitations & Challenges
[21]	Computational overhead; need for real-time validation in unstable datasets.
[22]	Limited real-world patient data; computational complexity.
[23]	Bias in EHR data; limited generalizability beyond veterans.
[24]	Lower accuracy compared with advanced methods; limited handling of unstructured data.
[25]	Performance sensitive to CGM sensor lag and calibration quality.
[26]	Predominantly in silico validation; need for clinical trials.
[27]	High power consumption of LSTM models on low-end wearable devices.
[28]	Limited personalized data; model complexity.
[29]	Retrospective nature of datasets; need for prospective conflict-zone data.
[30]	Review-focused; no new empirical data; clinical effectiveness depends on the underlying technologies and evidence reviewed.
[31]	Similar to [26]; limited ability to predict non-routine events.
[32]	Small sample size; unspecified study-specific limitations.
[33]	Small sample; veteran-centric focus.
[34]	Retrospective design; potential confounding bias.
[35]	Unspecified limitations; primary-care focus.
[36]	Low participant engagement; internet connectivity issues; high costs.
[37]	Recommendation-focused; no empirical data.
[38]	Dependence on patient adherence; short CGM duration.
[39]	Short study duration; population-specific focus.

[40]	In silico simulation; need for real-world validation.

Table 3. Categorization of Included Studies According to Their Relevance to Wartime Conditions

AI Technology Category	Primary Clinical Focus	Reference Numbers
Predictive Analytics (ML/DL)	Glucose level forecasting & Hypoglycemia alerts	[22], [23], [25], [26], [28], [31], [40]
Diagnostic Support	Early detection of complications (Kidney, Retinopathy)	[21], [24], [27], [29]
Digital Education & Support	Self-management, Chatbots, Virtual Coaching	[30], [32], [33], [38], [39]
Remote Monitoring (RPM)	Tele-management & Virtual Clinics	[34], [35], [36], [37]

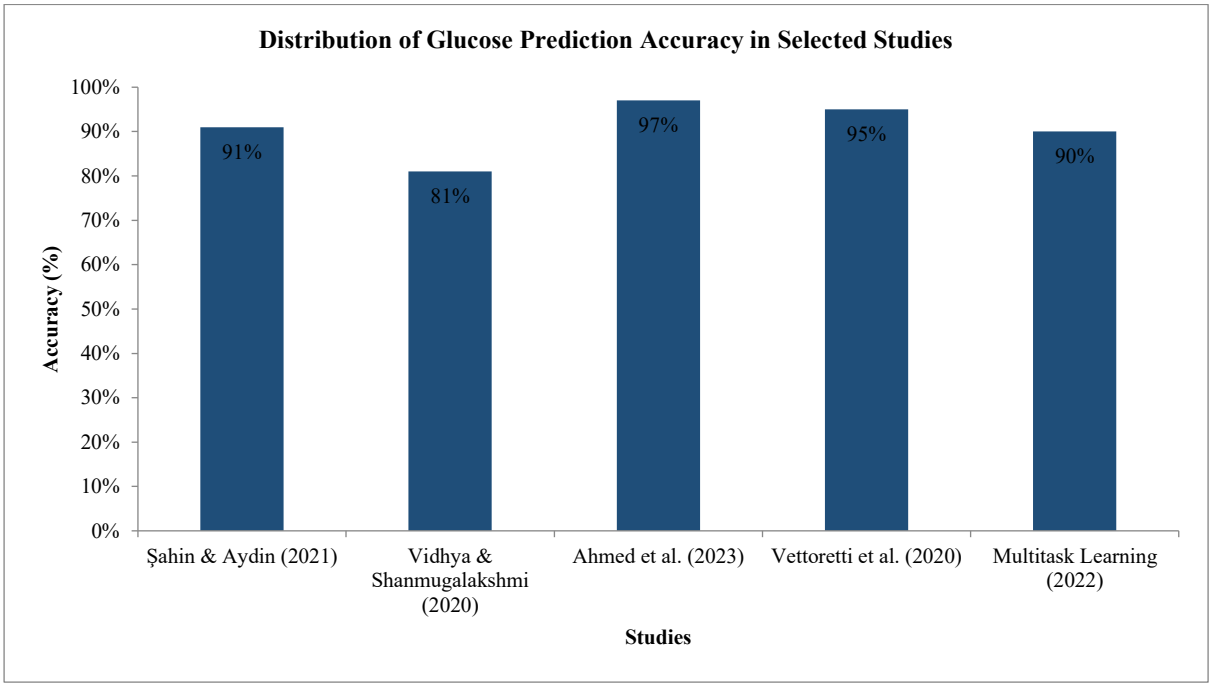


Chart 1. Distribution of Glucose Prediction Accuracy in Selected Studies.

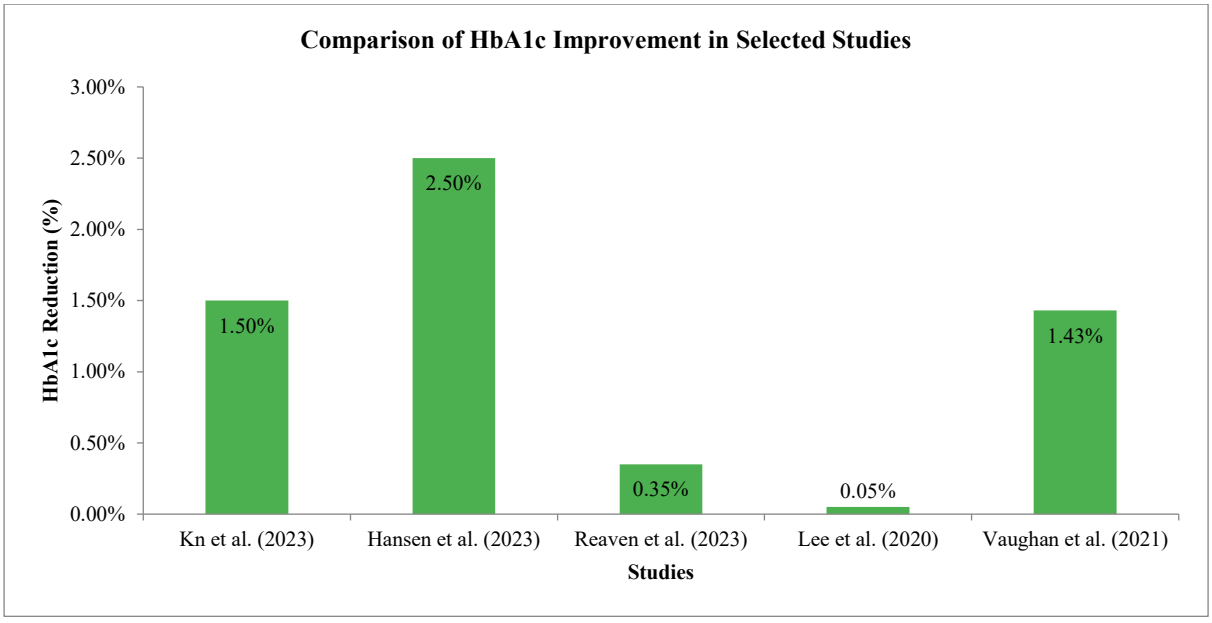


Chart 2. Comparison of HbA1c Improvement in Selected Studies.

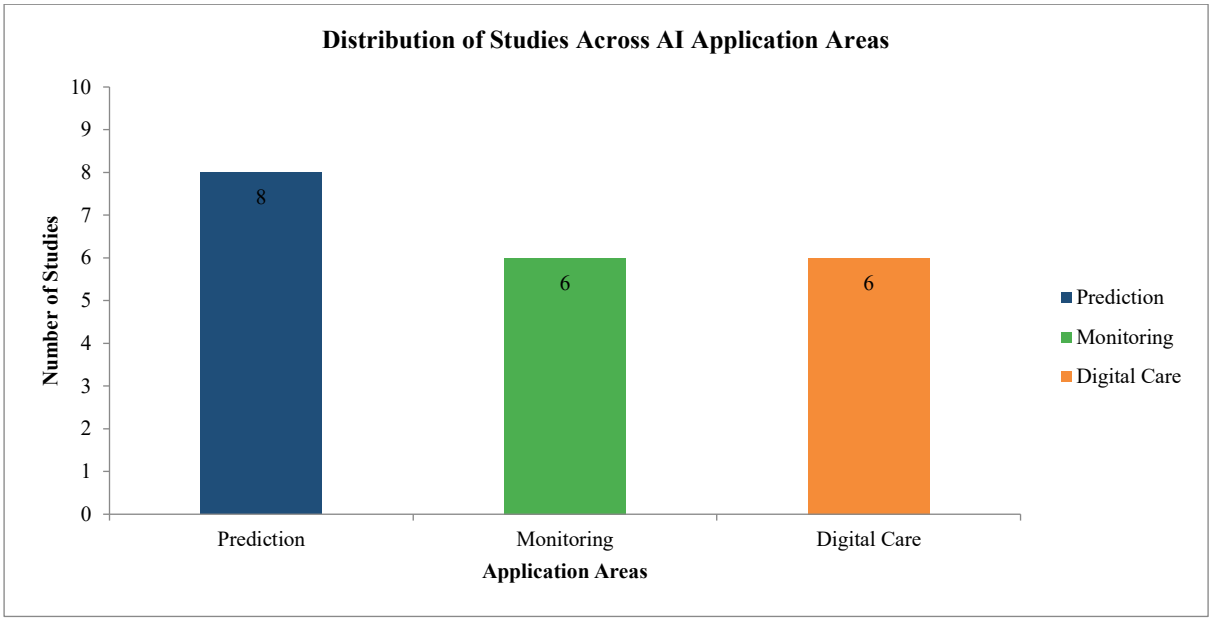


Chart 3. Distribution of Studies Across AI Application Areas.

Discussion

The findings of this systematic review indicate the transformative potential of artificial intelligence (AI) in diabetes management, particularly in crisis settings such as war, where access to traditional medical services is limited. The selected studies in Table 1, which focus on predictive models, continuous monitoring, digital education, and digital care, emphasize that AI can mitigate the unique challenges faced by diabetic patients in high-stress environments. For example, machine learning models for predicting blood glucose levels—such as advanced neural networks that forecast glucose up to 60 minutes ahead with a mean error of 18.81 mg/dL [22]—enable remote monitoring, which is vital during wartime when patient displacement and shortages of medical equipment are common. This approach may help reduce the risk of hypoglycemia. The integration of wearable sensor data, including photoplethysmography (PPG) and near-infrared (NIR) signals, may also improve predictive performance [25]. However, its suitability as an alternative to conventional monitoring methods in remote conflict-affected regions requires further validation. Additionally, deep learning models for predicting type 2 diabetes complications, with an accuracy of 81.20% in identifying complications such as nephropathy and retinopathy [24], demonstrate AI's capacity for early detection, which could reduce mortality in wartime conditions where stress and lifestyle changes heighten the risk of complications. AI-based educational tools, such as interactive chatbots and digital learning programs, provide personalized education and psychological support, helping patients strengthen diabetes management skills in wartime settings, especially where access to human educators is limited [5, 8]. These findings are consistent with other studies that have examined statistical models and non-classical biomarkers for precise prediction of complications with a C-statistic up to 0.89 [27], underscoring that AI can facilitate the prioritization of care in humanitarian crises where medical resources are scarce.

In the domain of continuous monitoring, the application of AI with CGM systems is notable, wherein machine learning algorithms compute insulin and predict glucose with an RMSE of 19–20 mg/dL and reduce the risk of hypoglycemia [26, 31]. A retrospective study involving veterans reported an association between CGM initiation and improved glycemic control, including a reduction in HbA1c of 0.35% and a lower risk of hypoglycemia [34]. However, these findings cannot be directly generalized to populations living in active conflict zones. Indeed, remote monitoring programs with nutrition coaching and telemedicine have reported improved glycemic control in primary care [35], which could be implemented during war—when physical clinics are destroyed—via mobile applications. Moreover, multitask learning approaches for personalized glucose prediction [28] and reinforcement learning models for glucose control with high interpretability [40] indicate progress toward automated therapies that, in war environments with a shortage of specialists, could manage insulin without the need for human intervention. These capabilities align with reviews of diabetes technology that describe AI as a tool for improving glycemic control in closed-loop systems [30] and suggest that integrating these technologies can increase access to care in occupied areas where diabetic patients are often deprived of medication supply chains. AI-based educational tools, such as digital learning programs integrated with CGM, facilitate nutrition education and self-management, helping patients in wartime conditions cope with food shortages and psychological stress [38, 39].

However, the application of AI in diabetes management during war is accompanied by challenges noted in the selected studies. For instance, hypoglycemia prediction models based on EHR data may carry bias and

may not generalize to non-veteran populations [23], a problem that intensifies in wartime settings where populations are diverse and data are incomplete. Moreover, the accuracy of deep learning models may be lower due to limitations in handling unstructured data [24], and predominantly in silico validation requires real clinical trials [26, 40], which are difficult to conduct in war zones. Study heterogeneity and the infeasibility of meta-analysis [25] also hinder strong generalizations, especially in different cultural contexts such as the Middle East or Eastern Europe, where socio-economic factors influence diabetes progression. In addition, AI-based digital care programs, such as virtual clinics [37], may depend on patient adherence and face internet connectivity problems during war [36, 38], increasing the risk of inequitable access. Studies indicate that reductions in HbA1c in virtual programs—such as 2.5% in veterans [33] or 1.43% in integrated telehealth care [39]—are promising, but small sample sizes and a focus on specific populations [32, 33] introduce limitations that must be addressed in wartime, where millions are displaced. Furthermore, predicting complications with AI models [29] carries a risk of bias, and the lack of standardized definitions of complications [27] can reduce accuracy in critical settings. Challenges related to AI-based educational tools, such as the need for stable internet connectivity and cultural sensitivity in educational content, must also be considered in wartime conditions, where cultural diversity is high [5, 36]. These challenges emphasize that AI must be integrated with ethical considerations, such as safeguarding data privacy in war zones where digital surveillance may intersect with security concerns.

The future outlook for AI in assisting diabetic patients during war focuses on the development of more robust models. For example, expanding personalized predictive models [28] to real crisis data can improve accuracy, and integration with CGM-based digital nutrition platforms [38] can facilitate nutrition management amid food shortages. Moreover, recommendations from the international panel for virtual clinics [37] suggest combining AI with team-based telemonitoring [36], which can be implemented in modern wars such as in Ukraine, where mobile technologies are vital. Future research should focus on longitudinal studies in war zones to evaluate AI's impact on reducing hospitalizations and mortality, and to validate reinforcement learning models [40] for automatic insulin adjustment under stressful conditions. Additionally, examining multi-complication predictive models [21] can help identify concurrent risks, and integrating biomarkers [27] can increase accuracy in vulnerable populations. Future research should focus on developing AI-based educational models that provide personalized education and psychological support for diabetic patients in crises, such as expanding educational chatbots to cope with wartime stress [8, 40]. Ultimately, policymakers should emphasize equitable access, because while AI can bridge existing gaps in diabetes care, without digital infrastructure it may exacerbate inequality. This review shows that AI is not merely a technical tool but a strategic solution for maintaining health during war, and—with rapid advances in technology—it has the potential to reduce the global burden of diabetes.

Conclusion

Ultimately, this systematic review indicates that AI can bring a profound transformation to diabetes management in wartime. With capabilities for accurate glucose prediction, remote monitoring, and early complication detection, AI reduces the risk of hypoglycemia and long-term complications such as retinopathy. Selected studies emphasize that machine learning and smart CGMs make patients more resilient against medication shortages and displacement. AI-based educational tools strengthen self-management and provide psychological support in crisis conditions. By integrating into digital platforms, these technologies enable virtual clinics to ensure continuous care even in occupied areas, reducing the economic burden on health systems. AI-based technologies may provide additional support for diabetes management when conventional healthcare services are disrupted.

However, harnessing this potential requires addressing challenges like data scarcity in war settings and privacy issues. Future research should focus on developing AI models robust to data noise and implementable on low-cost devices to ensure equity of access in low-income countries. Prioritizing culturally sensitive educational content and psychological support is essential. In conclusion, AI may contribute to more resilient models of diabetes care during humanitarian emergencies, provided that issues related to data quality, infrastructure, privacy, and equitable access are adequately addressed.

Data Availability

All data analyzed in this systematic review were obtained from previously published studies and publicly available sources cited in the manuscript. No new primary dataset was generated. The data extracted and synthesized for this review are presented in the article and its supplementary materials, where applicable.

Conflict of Interest

The authors declare that they have no competing interests or conflicts of interest related to the publication of this manuscript.

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Authors' Contributions

Mostafa Kashani and Sedigheh Barzekar contributed to the conception and design of the study. Both authors participated in the literature search, screening and selection of studies, data extraction, and methodological quality assessment. Mostafa Kashani contributed to data synthesis, interpretation of the findings, preparation of tables and figures, and drafting of the initial manuscript. Sedigheh

Barzekar contributed to the interpretation of the results and critically reviewed and revised the manuscript for important intellectual content. Both authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

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