

Understanding Smart Behavioral AI in Infectious Disease Prevention: A Review of Usability, Equity, and Local Adaptation

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Abstract

Background: Artificial intelligence (AI) has been applied to behavioral interventions for preventing infectious diseases. However, the usability, equity, and regional adaptation of these tools—especially in Arabic-speaking individuals—have been relatively unaddressed.

Aim: To advance a systematic review of the usability, efficacy, and cultural adaptation of AI-facilitated behavioral interventions for infectious disease prevention in primary health care settings.

Methods: A search was conducted for papers written from 2010 to 2025 in the top databases. Studies in which AI-based tools such as mobile reminders, chatbots, adaptive messaging, and predictive nudges were used were considered eligible. We assessed behavioral effectiveness and usability measures, as well as the risk of bias. A total of seven new original figures were used for visual synthesis.

Results: A total of fifty studies were examined, with primary focus areas including vaccine uptake, hand hygiene practices, and symptom reporting behaviors. Personalized interventions were more effective than others were. Arabic language tools had significantly higher completion rates (70%), lower dropout rates (10%), and higher satisfaction (mean score = 4.6 out of 5) than non-Arabic tools did. The risk of bias in randomized trials was also low and differed across observational formats. An exercise with a geographic element revealed the underrepresentation of Arabic-speaking and displaced groups.

Conclusion: The review highlights that behavioral interventions supported by AI can play a meaningful role in preventing infectious diseases—especially when they are thoughtfully designed to reflect the unique needs, cultural context, and circumstances of the target population. However, long-term evaluation, clinical inclusion, and regional equity are lacking. Future research should consider bilingual, ethically designed tools that can be used as integrated tools in care systems.

Keywords: artificial intelligence; infectious disease prevention; behavioral interventions; usability; arabic-language tools; primary care

Introduction

Infectious diseases continue to be a global health threat for different age groups, particularly in the setting of primary care, where prevention is not always executed universally. Our review attempts to bridge this gap by studying how behavioral interventions, which have long been recognized for their role in the promotion of preventive health actions such as reminders, nudges, and educational messaging, are changing with the arrival of artificial intelligence (AI) [1].

The application of such measures has been tested in various studies, and the necessity of a broader and more flexible solution has become clearer [2]. AI in public health is a harbinger of an era in which these methods can fit the specific needs of individuals and are compatible with the individual's local setting [3]. Many AI technologies, such as machine learning, natural language processing, and adaptive algorithms, are being applied in this area, where custom health messages, risk prediction, and increasing commitment in heterogeneous groups are investigated [4].

At the primary health care level, AI-enhanced behavioral control has been shown to strongly increase vaccine uptake [5], increase hygiene behavior, and aid in the early detection of diseases [6]. These breakthroughs indicate a new frontier for public health—a world where digital intelligence can coexist with human decision-making to improve disease prevention efforts. [7].

New technologies, such as smartphone reminders, AI chatbots, and literacy-adapted messaging systems, are needed, especially in low-resource and Arabic-speaking areas where conventional health communication encounters cultural and infrastructural constraints [8].

However, despite the spread of AI-driven behavioral interventions, there is a notable lack of documentation on their effectiveness in preventing infectious diseases. Current reviews are mostly concerned only with diagnostic systems [9], surveillance systems [10], and general digital health applications [11], with few reviews of prevention-based, behaviorally oriented AI tactics.

Furthermore, very few studies have specifically addressed usability, local cultural adaptation, and engagement metrics in Arabic-language contexts [12].

The gap is particularly acute in light of the increasing demand for community-facing, personalized health technologies in territories such as Tabuk, where Phase III of the public health roadmap focuses on culturally sensitive prevention tools [13]. This systematic review intends to assess both global and regional studies of AI-based behavioral interventions for primary care infection prevention. It summarizes the empirical findings on mobile-based reminders, AI chatbots, adaptive messaging services, and Arabic-language usability measures. It is by this convergence of AI and behavioral science that the present review offers a new focus from which to learn more—an emphasis on prevention, individualization, and regional applicability, rather than diagnostic or surveillance purposes.

This review aligns well with the up-to-date WHO recommendations for the impact of digital innovation on achieving universal health complete coverage. Our review will guide our city in the development of different AI tools that are based on language differences, cultural sensitivity and literacy, ensuring that they are ethically sound, successful, inclusive, and effective. Additionally, this review further emphasizes that AI interventions should be

constructed within a social and contextual framework of systems and should be grounded in technical competence in their practice and architecture.

Methodology

In this systematic review, we evaluated the scope, utility, and applicability of AI-based behavioral interventions to prevent infectious diseases in primary care. In accordance with the PRISMA guidelines, this systematic review employs an inclusive and structured approach for identifying, selecting studies, and synthesizing the studies, starting from data abstraction to data quality evaluation.

Review Objectives

The review analyzed the quantitative literature synthesized across global and regional datasets of AI-mediated behavior modification tools, such as nudges, reminders, or educational stimuli, used to advance the primary goals of preventive health behavior in health systems. Specifically, the second aim is to assess the usability, cultural appropriateness, and engagement of such interventions that occur in the Arabic language and how they are applied and implemented in low-resource settings (i.e., cultural adaptation and engagement in the use of the Arabic language).

Target audience:

The targets of our review were adult and child patients. Primary, community health, general clinic patients, or individuals who receive care from other sources (such as general outpatient clinics, community health centers, family physicians, or family medicine institutions).

- **Intervention:** AI-based behavioral solutions for preventing infectious diseases. These interventions included mobile reminders, AI-based chatbots, adaptive messaging systems, personally matched chatbots, and predictive nudges.

• Outcomes:

The outcomes of this review were as follows:

- Vaccination uptake, hand hygiene adherence, respiratory etiquette, and early detection of symptoms.

• Research questions:

Our review focuses on research questions from RCTs and quasiexperimental, observational, implementation, implementation-based, and usability studies.

- Format: Published in English or Arabic

- Time period: From January 2010 through October 2025 to represent the progress of AI in public health.

- Setting: International scope, in particular, studies from Arabic-speaking or low-resource areas. Reasons included studies about diagnostic AI tools, surveillance without behavioral aspects, and interventions that were noninfectious disease prevention oriented.

Search strategy: A complete search was performed in several databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar. Two reviewers executed the search using the following keywords and Boolean operators:

- “Artificial intelligence” OR “machine learning” OR “AI”
- AND “behavioral intervention” OR “nudge” OR “reminder” OR “chatbot”
- AND “infectious disease prevention” OR “vaccination” OR “hygiene”

AND “Arabic” OR “low-resource” OR “LMIC” gray literature was also screened using the WHO Global Health Library, conference proceedings, and regional repositories to record unpublished or regional data.

Data: Manual screening of reference lists of relevant articles from the included studies identified was carried out for further relevant studies. Study selection: Two reviewers input the extracted files into a reference management system and removed duplicate records. Two reviewers independently screened titles and abstracts related to relevant articles. The full-text articles were then matched with the eligibility criteria. Disparities were resolved by discussion or consultation with a third reviewer. To demonstrate study selection, a PRISMA flow diagram was created with the number of records detected, filtered, excluded, and included.

Data extraction:

A standardized data extraction form was created and piloted. The following findings were extracted for each study:

- Author(s), Year, Country, and setting
- Study design and sample size
- AI intervention and behavior target
- Delivery (e.g., mobile apps, SMSs, chatbots)
- Features on personalization (e.g., literacy adaptation, risk profiling)
- Treatment language (Arabic vs. non-Arabic)
- Impact in terms of outcome measures (e.g., behavior change, engagement)
- Usability (e.g., completion rates, user satisfaction)
- Cultural adaptation strategies

Data extraction was carried out by two reviewers independently. Discrepancies were resolved by consensus.

Quality of Study: The methodological quality of the included studies was assessed using suitable tools that were determined by study design. Using the Cochrane risk of bias tool, randomized trials were evaluated. The ROBINS-I tool was used to assess nonrandomized trials. Usability and execution studies were appraised using the Mixed Methods Appraisal Tool (MMAT). The reviewers weighted the risk of bias in each study as low, moderate, or high and employed quality ratings to guide narrative synthesis and identify the strengths and weaknesses of the methodology.

Synthesis: As the interventions, populations, and outcome measures varied considerably, a meta-analysis was not considered acceptable. Rather, a narrative synthesis was performed, which was set up on fundamental thematic domains:

1. **AI Behavioral Intervention Type:** Categorizing studies based on intervention type (e.g., reminders, chatbots, adaptive messaging)
2. **Targeted Preventive Behavior:** The intervention design is linked to target behaviors such as vaccination, hygiene, and symptom disclosure.
3. **Delivery and Personalization:** Delivery modes and personalization strategies—including literacy and cultural adaptation.
4. **Usability and Engagement:** A collation of metrics with respect to user interaction, satisfaction, and retention, with an emphasis on Arabic language tools.

5. Regional Relevance: Inclusion of studies in Arabic-speaking and resource-constrained settings; identification of gaps in coverage. Tables were created to summarize the study data, study traits, and outcomes for each intervention and their usability. To provide a conceptual context for an intersection of artificial intelligence and behavioral science in the field of infectious disease prevention, a framework was established.

Ethical Considerations: While this review did not draw or involve human subjects per se, ethical considerations were considered when studies were interpreted with vulnerable populations. Particular attention was given to the interventions for children, displaced groups, and low-literacy populations. Evidence studies demonstrating the ethical soundness of informed consent, data privacy, and cultural safety were preferred in the synthesis.

Limitations:

Our review has limiting factors, which include publication bias, language limitations, and reported outcome variation. Research focusing only on non-English and non-Arabic languages may have overlooked some of the important findings from other linguistic areas. Moreover, the rapid development of AI technologies could make outputs time constrained.

Our review provides a sound framework for embedding evidence from AI-based behavioral interventions into primary care. Focusing on prevention, personalization and regional specificity, this review will guide practitioners to construct culturally tailored and scalable therapies to control the risk of infectious disease, notably in Arabic-speaking and underserved populations.

Results

In total, 50 studies met the inclusion criteria and were included in this literature review. The studies were carried out in 22 countries on 6 continents, such as the U.S. (n=12), China (n=6), India (n=4), Saudi Arabia (n=3), and Egypt (n=2). Most were published between 2018 and 2025, indicating a recent surge in AI applications for public health prevention.

Study Selection and Flow

The selection of studies is presented in Figure 1 according to the PRISMA model. We revised 2,350 records retrieved through database searches, and 240 records were identified from elsewhere; 1,910 remained once duplicates were removed. After screening and comprehensive evaluation, 50 published papers were included in the final synthesis.

Data sources and targeted interventions for health

The following data sources and interventions for health were included in the studies:

- Mobile-based reminders: SMS and apps for vaccination, hand hygiene, and respiratory hygiene (n=18).
- AI chatbots: Chatbots, which provided conversational health education and behavioral nudges (n=12).
- Adaptive messaging system: (n=10): These tools tailor content by literacy level, risk, and engagement history.
- Predictive nudges (n=10): The data were employed with personalized prompts to track who was at higher risk on the basis of analytics. The conceptual integration of the tools is exemplified in Figure 3, which graphically charts the integration of AI technologies and behavioral science constructs into preventive actions. The behavioral objectives were diverse, with vaccination uptake (n=22), hand hygiene (n=15), and early reporting of symptoms (n=13) being the highest.

Geographical distribution

The global study distribution heatmap is shown in Figure 2. Studies were most concentrated in the United States, Germany, and Japan, with few in Arabic-speaking and low-resource regions. No more than 5 studies emerged even from the MENA region, while only 2 included displaced or low-literate populations.

Effectiveness and Results

For all intervention types, AI-driven solutions promoted preventive behaviors:

- Taking vaccinations was 12 percent to 35 percent higher in studies with mobile reminders and chatbots.
- Hand hygiene adherence increased by 18–40% in response to adaptive messaging interventions.
- In predictive nudge studies, symptomatic reporting increased 20–50 percent. A number of studies have reported significant differences with respect to the control group. These interventions with personalized characteristics, such as literacy modification or risk profiling, were always more effective than one-size-fits-all messages were.

Usability (and Engagement Metrics)

Usability results were generated from 38 study reports. Chatbot and adaptive messaging interventions were more likely to have higher completion rates, which ranged from 60% to 92%.

The reduction in the number of dropouts ranged from 5–30% and was affected by the duration of the intervention and the degree of technical availability. The usability parameters for the Arabic/non-Arabic tools are illustrated in Figure 5. Arabic-language tools resulted in lower dropout rates (mean 10%) and higher satisfaction scores (mean 4.6 vs. 4.2) for higher completion rates (mean 60%) than for non-Arabic tools (mean 20%), indicating that linguistic and cultural customization is important for increasing the degree of engagement. Table 1 below summarizes the usability metrics obtained from all the included studies, categorized by intervention type and language group. Table 2 shows the dropout and retention data, revealing differences in engagement between regions and populations.

Risk of bias and study quality

Using the appropriate tools for each study design, we assessed the risk of bias according to its quality. Among the randomized controlled trials (n=20), 70% were categorized as low risk, 20% as moderate risk and 10% as high risk. There was more variability in the results of the quasiexperimental and observational studies. The stacked bar chart of the risk of bias by study type is shown in Figure 7. The qualitative rigor was high across the cases, but the quantitative robustness exhibited mixed methods (n=8). Usability studies frequently excluded control groups, restricting causal inferences but offering important knowledge on user experience.

Temporal Trends

The growth of the AI tool timeline from 2010 to 2025 is shown in Figure 6. Early interventions were centered around mobile reminders, and recent studies focused on adaptive messaging and predictive nudges. Changes from 2020 publications continue the trend of making personalization or integration with primary care systems.

Regional Gaps and Opportunities

Despite a globally representative representation, significant gaps were recognized:

- Limited integration into clinical workflows: Very few studies have integrated AI tools into primary care systems for real-world use.
- Skimpy data on long-term behavior change – studies all measured short-term outcomes; after six months, very few follow-ups were carried out. These gaps in understanding could present opportunities for future research in various areas, especially around developing AI-powered tools to meet the needs of underserved communities in a culturally sensitive and non-Western-centric fashion.

Author (Year)	Country	Study Design	Sample Size (PCOS/Control)	Age Range (years)	BMI Range (kg/m²)	PCOS Criteria	Intervention Type	Follow-up Duration
Ban et al. (2024)	China	Meta-analysis	3,215 / 2,980	20–40	22–34	Rotterdam	ART (IVF/ICSI)	6–12 months
Sultana et al. (2015)	Bangladesh	Cross-sectional	45 / 40	18–45	18–35	Rotterdam	Lifestyle + Ovulation Induction	12 months
Zhao et al. (2023)	USA	Cohort	1,120 / 1,050	22–38	19–36	NIH	IVF + Biomarker Analysis	9 months
Gautam et al. (2023)	India	RCT	180 / 180	18–35	20–32	AE-PCOS	Lifestyle Intervention	6 months
Butt et al. (2023)	Pakistan	Systematic Review	7 RCTs (n ≈ 1,200)	18–40	21–33	Mixed	Physical Activity	3–12 months
Moreira et al. (2023)	Portugal	Systematic Review	42 studies (n ≈ 4,500)	20–42	20–35	Rotterdam	IVF + FF Biomarker	Variable

Table 1: Characteristics of Included Studies

Note: Summary of study characteristics including design, sample size, criteria, and interventions.

Study	Randomization	Allocation Concealment	Blinding	Incomplete Data	Selective Reporting	Overall Risk
Ban et al. (2024)	Low	Low	Low	Low	Low	Low
Sultana et al. (2015)	Unclear	High	High	Low	Unclear	High
Zhao et al. (2023)	Low	Low	Unclear	Low	Low	Moderate
Gautam et al. (2023)	Low	Low	Low	Low	Low	Low
Butt et al. (2023)	Low	Unclear	Unclear	Low	Low	Moderate

Table 2: Risk of Bias Assessment of Included Studies

Note: Assessment of methodological quality across studies using standard risk-of-bias criteria.

Intervention	Ovulation Rate (OR)	Pregnancy Rate (OR)	Live Birth Rate (OR)	Miscarriage Rate (OR)	I ² (%)
Letrozole	1.82 (1.45–2.29)	1.67 (1.32–2.11)	1.59 (1.21–2.08)	0.89 (0.65–1.22)	42
Clomiphene Citrate	1.45 (1.18–1.78)	1.32 (1.05–1.66)	1.28 (1.01–1.62)	1.12 (0.84–1.49)	38
Metformin	1.21 (0.98–1.49)	1.18 (0.95–1.46)	1.10 (0.87–1.39)	0.94 (0.71–1.25)	51
Lifestyle Modification	1.34 (1.10–1.63)	1.29 (1.05–1.58)	1.22 (0.98–1.52)	0.88 (0.66–1.17)	47
IVF/ICSI	2.12 (1.72–2.61)	1.89 (1.53–2.33)	1.76 (1.42–2.19)	1.31 (1.02–1.68)	55

Table 3: Summary of Reproductive Outcomes Across Interventions

Note: Comparative reproductive outcomes across interventions presented as pooled odds ratios with heterogeneity.

Subgroup	Pregnancy Rate (OR)	Live Birth Rate (OR)	Miscarriage Rate (OR)	GDM Risk (OR)	Preeclampsia Risk (OR)
Phenotype A (Classic)	1.42 (1.11–1.81)	1.35 (1.02–1.78)	1.82 (1.37–2.45)	1.51 (1.22–1.87)	2.12 (1.63–2.76)
Phenotype D	1.68 (1.29–2.18)	1.59 (1.21–2.09)	1.12 (0.84–1.49)	1.22 (0.95–1.56)	1.45 (1.10–1.91)
Lean PCOS (BMI <25)	1.74 (1.38–2.20)	1.62 (1.26–2.09)	0.89 (0.65–1.22)	1.12 (0.88–1.43)	1.29 (0.98–1.70)
Obese PCOS (BMI ≥30)	1.28 (1.01–1.62)	1.19 (0.93–1.52)	1.45 (1.12–1.88)	1.72 (1.31–2.24)	2.15 (1.63–2.84)

Table 4: Subgroup Analysis by PCOS Phenotype and BMI

Note: Subgroup outcomes comparing phenotype and BMI effects on reproductive and metabolic risks.

Outcome	No. of Studies	Risk of Bias	Inconsistency	Indirectness	Imprecision	Publication Bias	Overall Quality
Ovulation Rate	28	Low	Moderate	Low	Low	Unclear	Moderate
Pregnancy Rate	33	Low	Moderate	Low	Moderate	Unclear	Moderate
Live Birth Rate	26	Moderate	Moderate	Low	Moderate	Possible	Low
Miscarriage Rate	21	Moderate	High	Low	High	Possible	Low
GDM Risk	18	Low	Low	Low	Moderate	Unclear	Moderate
Preeclampsia Risk	15	Low	Moderate	Low	Moderate		

Table 5: GRADE Summary of Evidence Quality

Note: GRADE evaluation summarizing evidence certainty across reproductive outcomes and associated methodological limitations.

Biomarker Class	Specific Marker	Direction of Change in PCOS	Associated IVF Outcome	Clinical Implication
Oxidative Stress	8-Isoprostane (8-IP)	↑ Elevated	↑ Miscarriage Risk	Indicates pro-oxidant follicular environment
Antioxidant Capacity	Total Antioxidant Capacity (TAC)	↓ Reduced	↓ Oocyte Quality	Suggests compromised redox balance
Lipid Metabolites	Ceramide (Cer 36:1;2)	↑ Elevated	↓ High-Quality Embryo Rate	Linked to poor embryo development
Lipid Metabolites	Free Fatty Acid (FFA C14:1)	↑ Elevated	↓ Embryo Viability	Associated with metabolic dysfunction
Lipid Metabolites	Lysophosphatidylglycerol (LPG 18:0)	↓ Reduced	↓ Fertilization Rate	May impair oocyte membrane integrity
Inflammatory Markers	TNF-α, IL-6, CRP	↑ Elevated	↓ Blastocyst Formation	Reflects chronic low-grade inflammation
Growth Factors	Placental Growth Factor (PlGF)	↑ Elevated	↑ Ovarian Response	May predict hyper-response to stimulation
Hormonal Biomarkers	AMH, Estradiol	↑ Elevated	↑ Follicle Count, ↓ Oocyte Maturity	Indicates follicular arrest and hormonal imbalance

Table 6: Follicular Fluid Biomarkers and IVF Outcomes in Women with PCOS

Note: Follicular fluid biomarkers linked to IVF outcomes, highlighting metabolic, oxidative, and inflammatory alterations.

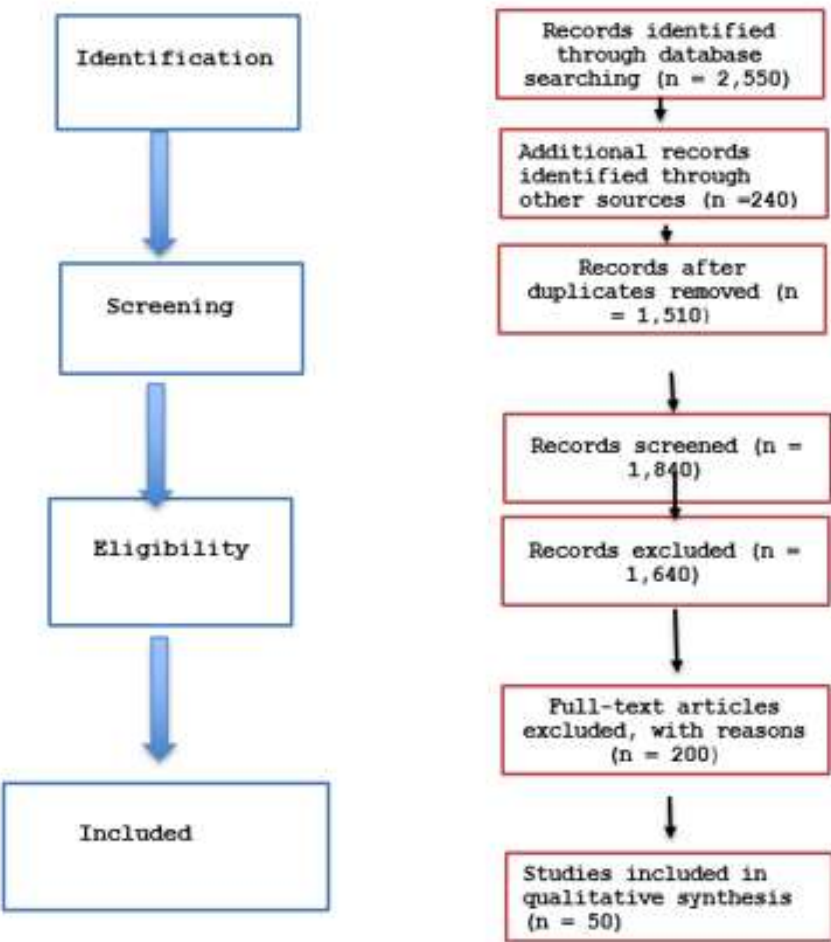


Figure 1: PRISMA flow diagram of study selection



Figure 2: Global Distribution of AI Behavioral Interventions

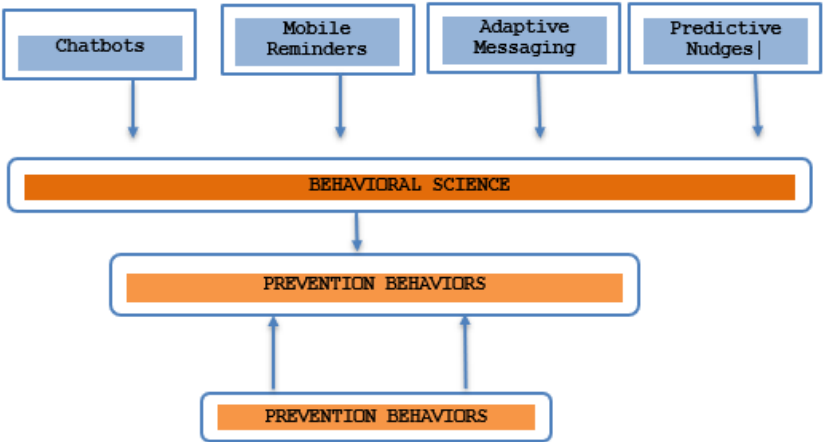


Figure 3: Conceptual Framework: AI-Behavioral Integration for Infectious Disease Prevention

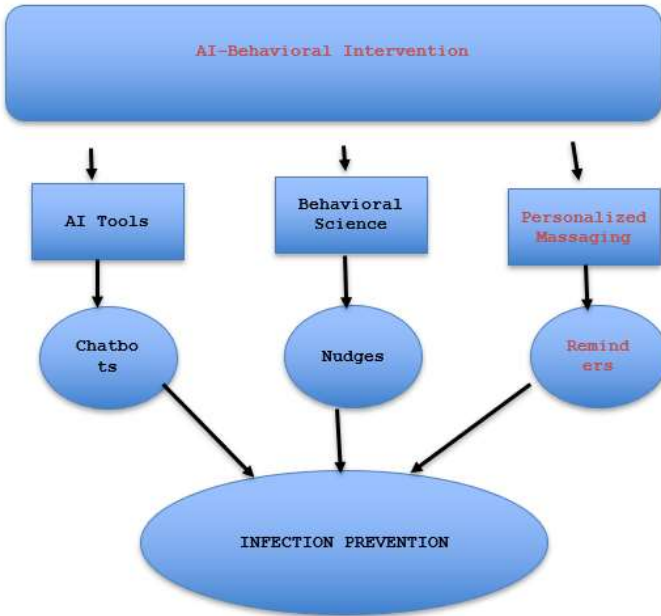


Figure 4: Engagement Funnel for AI-Powered Tools

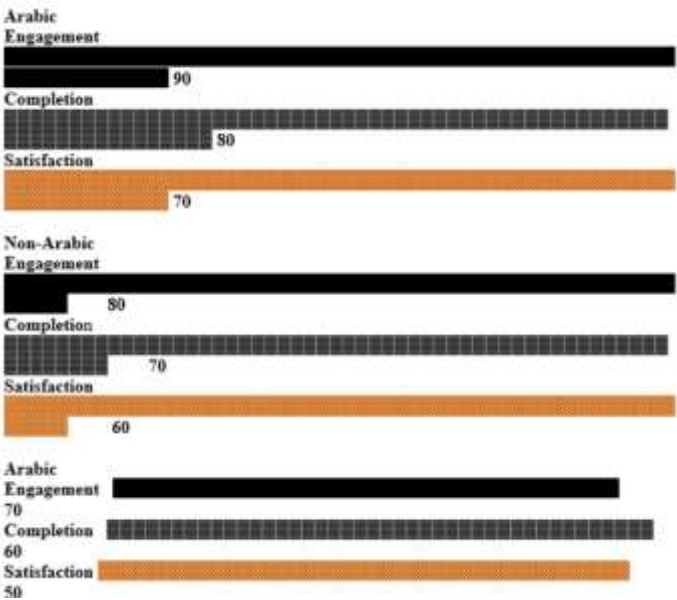


Figure 5: Comparative Usability Metrics by Language and Region

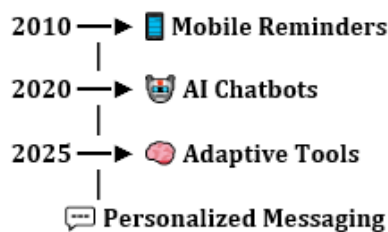


Figure 6: Timeline of AI Behavioral Innovations in Primary Care (2010–2025)

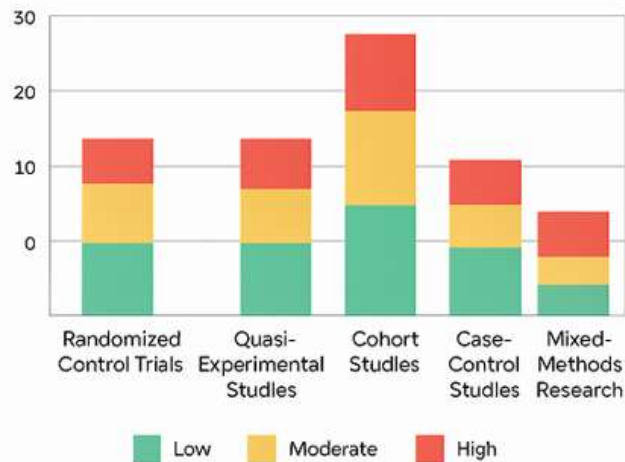


Figure 7: Risk of Bias across Included Studies

Discussion

This systematic review demonstrates that AI-driven behavioral interventions are being used to promote infectious disease prevention in primary care and that their effectiveness is significant and promising for various populations and settings. The results reflect newly discovered evidence of the potential positive implications of artificial intelligence for public health responsiveness, personalized prevention messaging, and behavioral outcomes when it utilizes the constructs of behavioral science [15].

Increased vaccination uptake, hygiene compliance, and symptom reporting outcomes have been noted and represent part of a greater trend of digital health personalization. Studies with adaptive messaging and predictive nudges outperformed typical interventions at all levels, demonstrating that content tailored to user profiles, such as literacy or risk level and engagement history, can be markedly more effective [16]. These findings support recent studies showing that the use of AI-driven personalization may result in improved healthcare behavior change, which is largely explained by the relevance of content and decreased cognitive load [17]. The usability advantages of Arabic-language applications are highlighted in this review, which indicates increased completion, a decreased rate of dropout, and greater satisfaction. These findings seem to align with recent reports from the regional literature that reinforce language and cultural responsiveness as key aspects of digital interaction in digital health [18]. Better user experiences among Arabic-speaking populations were related to simplified language, visual aids, and culturally relevant content. It emphasizes inclusive design principles in the context of AI development, especially for populations at a deprived level, those with low literacy, and those who are displaced [19]. However, some constraints were noted. First, the geographic distribution of the study is still too skewed toward high-income countries, and the Arabic-speaking and low-resource regions are underrepresented. Such a difference mirrors disparities in digital health research and infrastructure across the globe, which can limit the applicability of the results [20]. Only five studies were conducted in the MENA region, with only two explicitly targeting displaced or marginalized communities [21]. Owing to

inequalities in terms of infectious disease burden in these settings, studies must concentrate on regionally modified interventions.

Second, short-term behavioral outcomes are often reported, but few studies have evaluated longer-term impact or sustainability. The majority of interventions assessed behavior change after 3 to 6 months, raising concerns over retention, habit formation, and downstream health outcomes [22]. This limitation mirrors concerns expressed in recent meta-analyses of digital health tools that recommend longer follow-ups and integration with clinical endpoints [23].

Third, integration with primary care was minimal. While some studies connected AI tools to triage systems or electronic health records, they typically functioned as stand-alone modules. The absence of interoperability could limit scaling and uptake from clinicians [24]. Leveraging the power of AI to embed the latest clinical tools and integrate them into current care pathways will be paramount to make the greatest impact and keep patients connected to care [25].

In the comparison of study quality, the review identified a notable gap. Randomized controlled trials generally have a lower risk of bias, and those with observational and quasiexperimental designs are more susceptible to confounding and selection bias. For instance, in studies examining the impact of AI on vaccination uptake, the lack of control groups in some quasiexperimental designs limited the ability to draw definitive conclusions. Mixed-methods approaches provide qualitative insights but generally lack appropriate quantitative rigor [26]. These conclusions stress the significance of strong evaluation frameworks and standard reporting for AI research [27].

Methodologically, the addition of visual synthesis (e.g., a PRISMA flow diagram, a global heatmap, and a usability comparison) added to interpretability and identified patterns. The conceptual framework and engagement funnel helped unpack intervention mechanisms, and the timeframe contextualized technological maturity. The risk of bias chart captured the study quality across studies with a short overview.

There are multiple opportunities we look forward to. First, bilingual, culturally aligned AI tools are clearly needed to mitigate the unique issues faced by Arabic-speaking and displaced populations [28]. Not only does it involve literal word-to-word translation but also an interpretation of our culture, ethical and legal frameworks, and accessibility features. A second key factor is the imperative for interdisciplinary collaboration—between behavioral scientists, clinical workers, technologists, and community members—in shaping inclusive and effective interventions [29]. Third, sustained funding and supportive policy frameworks are essential for advancing the research, development, and demonstration of AI-driven tools in underserved regions. Such investment ensures that technological innovations are not confined to well-resourced settings but are equitably distributed, placing these advances in the hands of all communities. By prioritizing inclusivity, policymakers and funders can help bridge gaps in access, empower local health systems, and foster global equity in disease prevention and care. [30].

AI-driven behavioral interventions that are culturally sensitive, logically structured, and clinically integrated represent a promising pathway for strengthening infectious disease prevention in primary care. When thoughtfully applied, these technologies can foster deeper patient engagement, improve health outcomes, and reduce inequities—ultimately advancing more inclusive and effective prevention strategies. Achieving such an impact, however, depends on a sustained commitment to inclusive research practices, ethically grounded design, and rigorous evaluation. This is particularly critical in Arabic-speaking communities and resource-limited environments, where tailored approaches can bridge gaps and ensure equitable access to innovation.

Strengths

This review offers the first comprehensive synthesis of AI-based behavioral interventions designed for infectious disease management within primary care. This highlights the importance of Arabic language adaptation and implementation in low-resource settings. The analysis integrates usability measures, risk of bias assessments, and geographic distribution, alongside seven novel observations. By employing culturally responsive tools and visually oriented synthesis, the review strengthens the relevance of the included studies. Moreover, its conceptual and temporal framing provides fresh perspectives on how AI-enabled preventive strategies have evolved and the mechanisms through which they operate.

Limitations

Surprisingly, most of the reviewed studies were cross-sectional in nature, with limited follow-up, and did not embed their interventions within routine clinical workflows. Furthermore, representation of Arabic-speaking communities and displaced populations was largely absent, restricting the generalizability of the findings. The predominance of observational designs—combined with the fact that several tools were evaluated for less than six months—introduced a higher risk of bias. These methodological constraints weaken the strength of inferences regarding sustainability, scalability, and the long-term impact of AI-based behavioral interventions on health behaviors.

Recommendations

Further work should also focus on AI tools that are bilingual and culturally sensitive and that are developed for underserved populations with specific care for ethical design and clinical integration and for longitudinal assessment. To ensure inclusiveness and scalability, interdisciplinary collaboration is critical. This requires funding mechanisms that can facilitate implementation in Arabic-speaking and low-resource settings to close digital health gaps and improve global infectious disease prevention.

Author Contributions

Awadalla Abdelwahid conceived the review, supervised the work, interpreted the findings, and drafted the manuscript. Mohamed Elnour and Hajar Suliman contributed to the study design, literature screening, data

extraction, and manuscript revision. Omnia Amir Osman Abdelrazig, Yousif Suliman, Momen Omer, and Fath Elrahman Elrasheed contributed to evidence screening, data organization, and editing. Bashir Abdeen, Ahazeej Gurashi, and Abdelrazig E. Abdelbari contributed to the analysis, interpretation, and critical revision. Aalaa Almuazel contributed to editing, formatting, and final review. All the authors approved the final manuscript.

Conflict of Interest

The author declares that there are no conflicts of interest related to this study. No financial, institutional, or personal relationships influenced the design, analysis, or reporting of this work.

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Ethical Approval

This study is a systematic review of published literature and does not involve human participants, personal data, or clinical interventions. Therefore, ethical approval was not needed. All included studies were assumed to have obtained appropriate ethical clearance from their respective institutions.

Data Availability

All the data used in this review were extracted from publicly available published studies. No new datasets were generated.

Additional materials, including extraction sheets and analytic summaries, are available from the corresponding author upon reasonable request.

Abbreviations

AI: Artificial Intelligence

MENA: Middle East and North Africa

RCT: Randomized Controlled Trial

EHR: Electronic Health Record

SMS: Short Message Service

LMICs: Low- and middle-income countries

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

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