**AI-Driven Clearinghouse of Preventive Interventions Supporting Healthy Youth Development to Facilitate Evidence-Based Decision-Making**

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**Abstract**

Evidence-based decision-making applies empirical evidence to inform policies and involves integrating relevant information from various sources, such as scientific studies, experimental data, expert opinions, and community feedback. Online clearinghouses support evidence-based decision-making by synthesizing evidence on what works, though manually updating the literature is inefficient and incomplete. In addition, passively summarizing evaluations is insufficient for end-users to implement preventive solutions that achieve population impacts. A responsive, user-friendly platform and a dissemination plan are needed to encourage the uptake of equitable and culturally relevant preventive interventions grounded in transparency and rigorous evidence of effectiveness. The design of clearinghouses can significantly enhance evidence-based decision-making by building in stepwise, interactive, artificial intelligence (AI)-driven capabilities that harness machine learning for increased efficiency, reliability and comprehensiveness of evidence synthesis. AI algorithms with built-in safeguards to avoid unintended negative consequences such as biases and inaccuracies can make recommendations for up-to-date information on (1) the provision of all available evidence-based preventive interventions (EBPIs) and their key activities, (2) the equitability of EBPIs amenable to broad implementation and shown to achieve equitably distributed outcomes, (3) cultural relevance*,* including EBPIs that align with and respect the cultural beliefs, values, practices, and needs of a target population, (4) implementation support, such as materials, training, and fidelity measures, and (5) costs associated with delivery. The resulting platform will ethically expedite the translational process of identifying and scaling EBPIs, leading to a more complete, comprehensive and accessible body of evidence on effective preventive strategies. **Key Words:** artificial intelligence, clearinghouse, preventive interventions, implementation, evidence-based

**Introduction**

The scope and magnitude of challenges facing the United States – including COVID-19 that brought health problems and inequities to the forefront of public discourse – demand effective solutions that grant *all* individuals with access to the essentials needed for success (Buckley et al., 2023, 2024). Scientific evidence is a critical tool for revealing what works, in what settings, and for which individuals and communities (Fishbein et al., 2016). Evidence can protect taxpayer interests by informing decision-makers about where best to invest public dollars to ensure people who need help can secure it and to drive faster progress, thereby maximizing the ability of government funds to improve lives (Ellor, 2024). Evidence also identifies which strategies are most effective for specific populations and can therefore be a powerful tool for reducing disparities. By focusing efforts on programs that have been shown to work for historically disadvantaged groups, evidence can also help ensure that resources are allocated where they will have the greatest impact (Buckley et al., 2024).

Evidence-based decision-making emphasizes the use of data and rigorous findings of the best available evidence intersected with decision-makers’ expertise, community needs, and implementation context to inform choices. It involves systematically gathering, evaluating, and synthesizing relevant evidence from various sources, such as scientific studies, experimental data, expert opinions, and community feedback (Baba & HakemZadeh, 2012). Availing ourselves of opportunities for evidence-based decision-making to play out can be particularly impactful with the application of evidence amassed in the field of prevention science, which directs us to well-tested programs and policies shown to interrupt pathways to negative outcomes and improve the behavioral health and wellbeing among our youth (Fishbein & Sloboda, 2023).

Results for America is a nonprofit organization in the U.S. that helps government leaders harness data to solve challenges. The organization released a report detailing bipartisan progress made over the last decade to steer more dollars to evidence-based decision-making and help evaluate what works,including the Foundations for Evidence-Based Policymaking Act of 2018 that created a framework for evidence building (Ellor, 2024). Despite these advances, however, rigorous evaluation requirements have so far gained only a foothold in social policy and most government spending is still allocated with little regard to evidence about what works (Baron, 2018). The challenges have been in increasing the utility and awareness of what works, for whom, and in what settings so that this information can be more accessible, equitable, and applicable for communities, agencies, funders and policymakers.

To overcome these challenges, online clearinghouses were developed to provide free web-based syntheses of the evaluation literature by rating interventions based on their level of effectiveness to inform decision-making by communities, funders, policymakers and practitioners (Buckley, 2024). Clearinghouses, however, require significant human effort to screen the literature for relevant studies and to review and organize this information for users. This paper outlines a two-part framework describing how online clearinghouses can leverage artificial intelligence (AI) and related technologies to accelerate the translational process of identifying and scaling evidence-based preventive interventions (EBPIs). And how AI can be built into a clearinghouse to expedite the review process and increase its utility is exemplified using Blueprints for Healthy Youth Development, i.e., Blueprints (Mihalic & Elliott, 2015), the only online clearinghouse solely focused on synthesizing and platforming EBPIs.

**Online Clearinghouses of Evidence-Based Interventions**

Online clearinghouses are one tool for identifying and disseminating information on what works for whom and in what contexts. They serve as repositories of reports synthesizing the effectiveness of behavioral interventions for infant, youth and adult populations that fall under a wide range of disciplines and domains, such as criminal justice, child welfare, public health, mental health, education, and labor/employment, among others (Buckley, 2024; Horne, 2017; Neuhoff et al., 2015). These clearinghouses translate the evaluation literature and raise awareness about the existence of evidence-based interventions (EBIs; Buckley et al., 2020).

**Functions**

To identify which interventions are “evidence-based,” clearinghouses review intervention evaluations using published standards of evidence focused primarily on internal validity and evidence of effectiveness supported by randomized controlled trials (RCTs) or other quasi-experimental design studies (QEDs) using casual inference methods with requirements that intervention and control groups are comparable at baseline, attrition is minimal and not differential, and outcomes are assessed using reliable and valid instruments (Wadhwa et al., 2024; Zheng et al., 2022). Clearinghouse procedures typically involve (1) identifying RCTs and QEDs of social programs through literature searches; (2) assessing each study’s significance and internal validity, i.e., risk of bias assessment (Steeger et al., 2021); (3) representing evidence in a text form that is comparable across studies; (4) synthesizing evidence across evaluations by writing extensive and detailed reviews; and (5) presenting the synthesis online in (ideally) readily understandable and usable ways (Buckley et al., 2022; Buckley, 2024).

These clearinghouses provide a wealth of information, such as a description of the intervention and an effectiveness rating that is designed to allow users with minimal knowledge of research methods to select an evidence-based intervention or to vet interventions that have already been adopted (Burkhardt et al., 2015). Additionally, some online clearinghouses provide a written summary of costs, training, and/or the availability of technical assistance to assist with dissemination and scaleup (Buckley et al., 2020; Paulsell et al., 2017). Advantages of online clearinghouses in providing electronic publication include that evidence reviews: (1) are not constrained by lack of space; (2) can be updated as new information becomes available or when new ways of improving them are identified; and (3) can be cross-linked to other, related sources of relevant information (Starr et al., 2009).

**Proliferation**

The number of clearinghouses has grown prolifically over the past 30 years, many in response to states and governing bodies increasingly establishing funding mandates (i.e., the use of data-driven indicators for determining grant eligibility or requiring evidence to support funding decisions) to minimize the use of ineffective programs and limit unnecessary spending (Buckley, 2024; Horne, 2017; Lee et al. 2022). To date, up to 24 clearinghouses exist within the United States and Europe alone (Axford et al., 2022; Burkhardt et al., 2015; Mayo-Wilson et al, 2022). Included within this count is Blueprints as well as the individually operated clearinghouses associated with (currently) five different divisions of the U.S. Departments of Education, Health and Human Services, Justice, and Labor and one division of the U.S. Department of Defense, with all six administered by either U.S. federal government staff or contracted research organizations. These federal evidence clearinghouses are directly or loosely tied to U.S. legislation requiring the use of evidence to support federal funding requirements (Buckley, 2024; Mayo-Wilson et al., 2022).

The demands on online clearinghouses are greater than ever. They must assist entire fields – from public health and child welfare to mental health, education, labor and employment – in tracking an increasingly voluminous and scientifically complex literature on the effectiveness of policy and programmatic interventions for infants, children, adolescents, young adults, seniors, families, and communities. Research shows minimal overlap across U.S. clearinghouses in terms of the individual interventions reviewed (Wadhwa et al., 2024; Zheng et al., 2022), which reflects a need for the large number of clearinghouses given the vast amounts of evidence being generated by the social sciences. Consistent with other fields (e.g., medicine, physics, etc.), users cannot keep up with this volume of work, and many consumers do not have the time or expertise to assess which studies are of high quality and worthy of consideration when making decisions. Clearinghouses have become increasingly important, as the volume of relevant evidence expands, and with widely varying quality of the studies, even those in the peer-reviewed literature (Buckley, 2024; Mayo-Wilson et al., 2022).

A challenge remains, however, in providing sufficient resources and support for users to meaningfully engage in the use of research evidence (Mosely, 2023), including clearinghouse reviews. Although online clearinghouses were designed to simplify the task of selecting EBIs, their rise and expansion has caused confusion stemming from how they differ in (1) focus (i.e., one domain – such as the U.S. Department of Education’s What Works Clearinghouse (WWC)’s focus on student academic achievement – versus multiple domains, such as Blueprints’ focus on healthy youth development); (2) modality (program, practice, or policy); (3) accepted designs (meta-analysis, only RCTs, certain QEDs, or no restrictions on acceptable designs); (4) benchmarks for when “slippages” in evidence standards (e.g., baseline equivalence and differential attrition) are problematic and likely to bias results, and (5) ratings (i.e., some clearinghouses rate interventions as “evidence-based” or not, while others rate interventions according to several “tiers” of evidence that explicitly require, for example, replication and/or sustained effects for a top tier rating (Buckley, 2024; Fagan & Buchanan, 2016; Means et al. 2015; Wadhwa et al., 2024; Zheng et al., 2022)). Although it is unclear why clearinghouses rely on different standards, criteria are likely influenced by political concerns, scientific debates and ideologies, and financial and other practical considerations (Fagan and Buchanan 2016; Means et al. 2015). In addition, online clearinghouses update their sites according to different schedules because the process for identifying and reviewing programs is so time consuming and expensive, causing concern about the timeliness of generating or updating evidence reviews (Burkhardt et al. 2015; Means et al. 2015). These challenges contribute to a messy evidence landscape and result in different levels of confidence regarding the effectiveness of interventions recommended for scale-up (Axford et al. 2022; Elliott et al. 2020). Thus, clearinghouses must clarify inconsistencies to reduce user confusion *and* simultaneously innovate to ensure their feasibility and relevance.

**Limitations**

In addition to collective user confusion as outlined above, several shortcomings of individual online clearinghouses were outlined in the Bridgespan Report on a study of the “What Works Marketplace” (Neuhoff et al., 2015). Accordingly, they are not as widely utilized as the evidence warrants, limiting their impact in communities. First and perhaps foremost, while Lee et al. (2022) found that important user groups are accessing certain clearinghouses, and that these clearinghouses are useful to the types of users (e.g., grant writers, practitioners, and some agency directors) who access them, online clearinghouses are not easily navigated by most end-users (e.g., community groups, practitioners, policymakers). The literature (while limited) suggests that online clearinghouses are not well understood or easy to navigate, especially by legislators and regulators charged with making policy (Burkhardt et al., 2015; Lee et al., 2022). Second, clearinghouse administrators are required to routinely manually update the literature—a process that is inefficient and incomplete. Third, passively viewing evaluation summaries of prevention strategies is not an effective vehicle for transmission to communities, policymakers, and other decision-makers to engage users in implementing evidence-based solutions that achieve population impacts (Lee-Easton et al., 2022). Fourth, users have only unidirectional access to online clearinghouses which limits their utility. That is, filters defined by clearinghouse staff allow users to search for interventions based on outcome (e.g., problem behavior such as substance use or delinquency; as well as positive development such as educational attainment, emotional well-being, physical health), target population (e.g., age, sex, gender, race, ethnicity), and program specifics (e.g., program type, program setting). Users click one or more of these filters to generate a list of interventions and studies reviewed that meet all the criteria of these pre-defined filters, however there is no bidirectional interaction to reach an optimal solution. And fifth, as mentioned previously, clearinghouse reviews generally focus on internal validity (the ability to make causal inference; Wadhwa et al., 2024; Zheng et al., 2022); however, they lack information on how to consider transparency, cultural context and health equity (Buckley et al., 2024; Hirsh et al., 2023; Newcomer et al., 2023).

Given growing concerns related to the applicability of causal inferences, users want information on the reporting of health equity in RCTs (e.g., whether benefits are concentrated among those who are already advantaged) and cultural relevance (i.e., how well the intervention aligns with and respects the cultural beliefs, values, practices, and needs of a target population; Newcomer et al., 2023; Strayhorn et al., 2024). They also want the ability to identify innovative and community-developed programs in publication but have yet to be subjected to rigorous evaluation (Martinez et al., 2010). And having open access to the research materials (e.g., outcome measures used, intervention manuals, etc.), the anonymized data collected, and the scripts (i.e., code) used to analyze data is valuable, as transparency and reproducibility have long been recognized as vital functions of science (Buckley et al., 2022; Mayo-Wison et al., 2022).

The Bridgespan Group conducted interviews on both the supply and demand sides of interventions and identified six gaps impeding the utility and reach of evidence-based knowledge, summarized as follows. (1) Comprehensiveness: Decision-makers want information on a broader range of interventions with varying levels of effectiveness. They also want to know which interventions are promising or have not been reviewed or rated; (2) Implementation: Decision-makers want information about interventions beyond evidence of impact—including peer experience implementing the intervention—to help them make informed decisions. Few clearinghouses provide this level of information.(3) Guidance: Decision-makers are looking for guidance and support in selecting and planning to implement the appropriate intervention. Existing clearinghouses, however, are not set up to provide guidance, and intermediaries in this space are still relatively limited.(4) Synthesis: Decision-makers are looking for more than just EBIs. They also need “smart” practices as well as information on policies and management decisions. This information is not currently available; existing clearinghouses rely on traditional search engines that are not intuitive, interactive, or readily customizable; (5) Usability: Users do not find clearinghouses easy to use, nor do they understand the differences between them (e.g., in terms of content, ratings, breadth of topics, populations, etc.);(6) Awareness: Decisionmakers receive information about interventions from purveyors and peers, but they do not often receive information about interventions provided by objective sources or delivered in a user-friendly platform (Neuhoff et al., 2015).

**Improving Clearinghouse Functionality Via AI**

To address clearinghouse shortcomings and gaps in awareness of the vital resource offered by online clearinghouses (Neuhoff et al., 2015), a responsive and comprehensive literature review process, platform, and dissemination plan are needed to encourage the uptake of wise practices grounded in rigorous evidence of effectiveness. Herein, we propose that artificial intelligence (AI) is a valuable technology to facilitate the process of identifying, selecting, and implementing EBIs for greater accessibility, instructiveness, and reach by end-users (e.g., community partners, practitioners, local agency officials) and, in turn, improving decisions and investments by funders, including policymakers and taxpayers. AI, broadly speaking, refers to the efforts of computers in mimicking human understandings and problem-solving abilities (Voss, 2024). Below, we provide an overview of how AI has been implemented in ways that create possibilities to improve the functionality of online clearinghouses and thus promote evidence-based decision-making.

**Living Systematic Review**

A relatively new synthesis method is called a “living” systematic review, wherein research articles and reports are updated as new findings become available and relevant evidence is incorporated into the review. Unlike traditional systematic reviews, which are typically static and updated manually at unspecified intervals or after long periods of time, living evidence reviews synthesize and update evidence in shorter, predetermined intervals, allowing the public to access current findings and data on a given topic. Within the living evidence review approach, various AI tools are used to automate the monitoring of new research publications, such as web scrapers, RSS feeds, or automated alert systems (like PubMed and Google Scholar alerts) that index new studies related to specific topics. Meanwhile, machine learning and advanced algorithms can assist in the identification of relevant studies and extract data from publications. These technologies help in scaling the review process and increasing the comprehensiveness of information included in the review. Many living evidence reviews are made accessible through web interfaces that present the findings in an understandable format. This may involve data visualization tools that keep track of changes made to the review, ensuring that users can see how the evidence evolves over time and trace back to earlier versions if needed (Chakraborty et al., 2024; Rojas-Reyes et al., 2024). The living evidence approach has been embraced globally, with the World Health Organization, Cochrane Collaboration, and Pan American Health Organization all committing to adopting living evidence approaches (Chakraborty et al., 2024).

**ChatGPT**

A Large Language Model (LLM) is a type of AI that is designed to understand, generate, and interact with human language. LLMs are part of the field of Natural Language Processing (NLP), a branch of AI focused on the interaction between computers and human language. NLP includes tasks like understanding and generating text, translating languages, answering questions, summarizing content, and more. The usage of LLMs has grown exponentially in recent years and may have great import for the usability of online EBI clearinghouses.

One such model, ChatGPT (Generative Pre-trained Transformer), a human preference-aligned chat bot from Microsoft-backed OpenAI, has garnered significant attention by the public since its launch in November 2022 (Scarlatos, 2024). ChatGPT is the equivalent of a giant library where LLMs (which are the core of ChatGPT) have read all available texts and learned patterns in how words and sentences are formed to predict the next word or sentence. So, when a user asks ChatGPT a question or prompts it, ChatGPT predicts the most likely response based on its knowledge of language and patterns it learned from all the information it processed. ChatGPT therefore engages users in an interactive dialogue, encouraging them to ask questions and explore topics more deeply (Alghizzawi, 2024; Gartlehner et al., 2024); a feature that could facilitate decision-making based on all available evidence-based information and provide more personalized implementation guidance for clearinghouse users.

ChatGPT has shown promise in the field of education. For example, a recent trial tested the impact of ChatGPT-assisted lesson and resource preparation on teacher time, with implementation support via a guide for teachers, against approaches unassisted by AI. Teachers randomly assigned to the ChatGPT group reported experiencing significantly lower lesson and resource preparation time than the comparison group of teachers. Meanwhile, quality did not appear to be affected according to an expert panel reviewing the quality of lesson resources, blinded to which had been produced using ChatGPT (Roy et al., 2024). Still, more research is needed to understand the full potential of ChatGPT, including how the technology can support learning and decision-making across multiple fields. The advantages of leveraging ChatGPT, such as scalability, efficiency, and the ability to process massive amounts of data, however, need to be considered along with the potential risks associated with this evolving technology.

**Risks**

For all the potential benefits, the risks could cause more harm than good in the absence of the proper safeguards. For example, these AI models have been known to make factual errors, often referred to as “hallucinations,” that could result in users receiving false or misleading information. In addition, the responses generated by ChatGPT lack real-time expertise and accuracy. As a language training model, ChatGPT does not possess genuine understanding of the knowledge it produces. ChatGPT has a natural advantage in content generation, as it autonomously creates conversational content based on user prompts, bypassing the overreliance on traditional knowledge production by professionals. However, its ability to generate responses relies on a large amount of “input data,” which may contain biases and discrimination. Furthermore, there is the issue of potential personal privacy leakage. Although ChatGPT does not directly collect users’ personal information, the internet connections used may store users’ chat records on servers. This means that when users input questions into ChatGPT, data leakage can occur (Slattery et al., 2024; Zhang et al., 2024). Platforms that adopt ChatGPT and related AI technologies must therefore take these risks into serious consideration and develop protections to guard against the potential negative unintended consequences of AI.

**Exemplifying the Utility of AI Using a Well-Known Online Clearinghouse**

Like other clearinghouses, Blueprints synthesizes EBIs, which are programs, practices, or policies grounded in empirical evidence derived from high-quality research studies that support their efficacy, effectiveness, and safety (Gottfredson et al., 2015). Blueprints, however, is the only online clearinghouse solely focused on synthesizing evidence-based preventive interventions (EBPIs), which share attributes of EBIs. The term “preventive”, however, underscores their proactive nature. Also referred to as “upstream preventive programs,” EBPIs intervene before problems occur or escalate to reduce the burden of disease and dysfunction on individuals, families, communities, and societies (Boyd et al., 2023; Fishbein & Sloboda, 2023).

Although the framers of Blueprints regularly conduct upgrades, there is a need now to functionally advance and address many of the same limitations of other clearinghouses to deliver on their purpose, as outlined by the National Prevention Science Coalition to Improve Lives (<https://www.npscoalition.org/ebp-clearinghouse-proposal>). In this example, we present a plan to continuously update and systematically appraise Blueprints’ summaries of preventive intervention research evidence using AI. The Blueprints’ database could also be linked to networks of scientific partners who collectively disseminate resources on identifying, testing and scaling preventive interventions to outline the data infrastructure and its features. The result is a one-stop resource for current information and assistance needed to effectively deploy a range of evidence-based preventive strategies. We describe how new technologies and real-time transparent, equity-centered approaches can be leveraged to connect prevention science and implementation science within one AI-powered closed and trustworthy system to meet decision-makers’ needs for a more thorough and comprehensive suite of effective preventive strategies.

**Blueprints’ Current Operational Model**

To understand how AI can enhance Blueprints’ functionality, we first summarize the process of systematic reviews and features that allow for user interface. When Blueprints was launched in 1996, decisions to adopt policy and programmatic interventions were made largely without the benefit of research on their effectiveness. Blueprints was one of the earliest efforts to establish a clear scientific standard for evaluating the evidence of an intervention’s effectiveness, implementing a rigorous expert review process, and certifying those programs that met this standard (Buckley, 2024). Since then, Blueprints has gathered and publicly organized a wealth of citation-level information on the evidence base underlying 1,600 preventive interventions implemented world-wide that are aimed at supporting healthy youth development.

Blueprints was selected to launch the concept of an AI-powered clearinghouse because it is a trusted source of evidence-based preventive programs recommended for large-scale implementation that meet a high evidentiary standard, as cited in reports by Pew Charitable Trusts and the United Nations Office on Drugs and Crime & World Health Organization which refer to Blueprints by name as a leading exemplar (Caudell-Feagan et al., 2022, p. 11; International Standards on Drug Use Prevention, p. 42). Blueprints earned its stellar reputation as a function of its independence; i.e., it does not receive funding from any interventions that it reviews, nor does the clearinghouse fund the adoption or scaleup of any EBPIs listed on its website. And Blueprints applies transparent standards when assessing study quality, as well as the importance (or magnitude) of the impacts reported by these studies.

Blueprints currently judges an intervention’s evidence base according to four criteria, which are consistent with evaluation guidelines recommended by the Society for Prevention Research (Flay et al., 2005; Gottfredson et al., 2015). They include, (1) Intervention specificity: All programs must clearly identify the theory(ies) guiding the intervention, their targeted risk and protective factors and outcomes, the populations to be served, and their specific delivery methods. (2) Evaluation quality: Evaluation studies must implement a strong group design and sound statistical analyses. Blueprints staff and advisory board conduct a risk of bias assessment to highlight potential flaws or limitations in the study design and analyses that could affect the validity of results (Steeger et al., 2021). (3) Intervention impact: The preponderance of evidence must show consistent, statistically significant, and positive effects on outcomes, with no harmful effects. (4) Dissemination readiness: Programs must be available for use, with instructions (e.g., manuals, training) to guide implementation, a list of costs associated with dissemination (such as those for start-up, implementation, and support), and an explanation of staff resources (e.g., staff qualifications and time commitments) needed to deliver the intervention (Buckley et al., 2020).

# **Enhanced Clearinghouse Functionality Via AI**

To guide significant enhancements to the Blueprints infrastructure, we propose a two-part framework. If adopted, the most current and comprehensive information could be provided on a range of EBPIs on a more intuitive, personalized, and user-friendly interface.

**Part I: Living Evidence Framework**. The first part of this framework involves harnessing machine learning to create a “living evidence” framework that enhances efficiency and reliability of Blueprints’ literature search and data extraction processes to ensure that the Blueprints database is continually updated to incorporate new and relevant evidence when it becomes available (Gartlehner et al., 2024; Turner et al., 2023). Large Language Models (LLMs) could be used to increase efficiency of Blueprints literature search strategy, replacing the manual process of (1) entering multiple search terms into individual search engines and individually reviewing abstracts for eligibility, (2) searching blogs, other clearinghouse websites, and web pages of research organizations to identify additional studies, and (3) accepting nominations from developers and/or researchers. This activity not only facilitates the Blueprints process of garnering and organizing a large body of information, it also significantly enhances comprehensiveness of that information – ensuring information is updated and relevant – which benefits end-users (Gap 1).

In addition, Natural Language Processing (NLP) could be incorporated into the labor-intensive Blueprints review process to replace manually extracting data from primary studies into standardized tables. For example, NLP algorithms could extract from reports and articles the intervention’s description, study setting, sample characteristics, outcomes, and effect sizes (etc.). These algorithms could also replace Blueprints’ labor-intensive queries to examine the readiness of the intervention for dissemination by extracting publicly available information on materials, training, and costs associated with implementation and staff resources needed to deliver the intervention, including policies and management systems to be in place for the intervention to be implemented with fidelity. Blueprints reviewers could validate and cross-check the extracted data to ensure accuracy, completeness, and consistency (Gartlehner et al., 2023). The Blueprints staff and board could also then conduct their standard risk of bias review (Steeger et al., 2021), which NLPs could be used to efficiently expand the evidence review criteria to also consider criteria assessing health equity and cultural relevance of interventions (Buckley et al., 2024; Hirsh et al., 2023; Newcomer et al., 2023) and transparent evaluation methods, such as preregistration and sharing of data/code/research and program materials (Buckley et al., 2022; Mayo-Wilson et al., 2022).

**Part 2: ChatGPT to Support Implementation Guidance**. The second component of this framework involves adding a search engine that would provide for the type of interaction via AI software (e.g., ChatGPT) that might occur in a conversation, where one statement or query leads to a more personalized, informative, accurate, and instructive response for providing contextual and operational follow-up. ChatGPT technology could serve multiple functions, as summarized below. We also briefly propose the need for a clear and comprehensive dissemination plan to improve awareness and reach.

First, ChatGPT could play an integral role in helping users navigate clearinghouses like Blueprints by allowing for conversations with human-like responses and interactions (Alghizzawi, 2024). It also can be used to automate various tasks performed by clearinghouse staff (e.g., responding to public inquiries), and effectively generate a breadth of on-topic questions in a variety of styles. Using generative AI, computer scientists could create algorithms and models using LLMs from emails between public users of the Blueprints website and Blueprints staff to learn patterns (e.g., types of information sought by Blueprints users) in generating new data following those patterns. AI-generated parameters and ChatGPT technology could then be used to improve user search efforts by mapping information on EBPIs stored in the Blueprints database to the specific questions posed by users. For example, users could be assisted in the selection of samples of evaluations reviewed by Blueprints to identify EBPIs that have validity with racially and ethnically diverse populations and rural communities. The primary advantage of these AI-generated parameters over Blueprints’ current structure is that navigation to find information on EBPIs within the Blueprints database would occur *incrementally* (to suit the user’s level of knowledge and experience), *flexibly* (as a bidirectional learning platform) and *interactively* (to reciprocally learn and generate responses of relevance to the user). This set of activities addresses Gaps 3, 4 and 5 of the Bridgespan report.

Second, ChatGPT software could be added onto a learning management system (LMS) that connects the Blueprints’ platform to other trusted scientific resources vetted by Blueprints to provide community assessment and implementation support of well-tested operational protocols that ensure feasibility, fidelity, acceptability, appropriateness, and sustainability. User inquiries could then be linked from the Blueprints platform to detailed guidance regarding how to select corresponding EBPIs that map to community needs. For example, responses to user questions concerning mapping community needs could be generated from the Communities That Care Youth Survey (CTCYS) that identifies high levels of risk and low levels of protection in communities, with survey results and explanations provided by Communities that Care (CTC) staff guiding prevention efforts around which interventions to adopt (Briney et al., 2012). These links could also connect users’ inquiries to recommendations for implementation procedures via the Prevention Learning Portal (<https://plp.psu.edu/>) which serves as a one-stop website for prevention resources, training, and self-paced learning programs, funded by the Pennsylvania Commission on Crime and Delinquency (PCCD) and provided by Penn State’s Evidence-based Prevention and Intervention Support Center (EPISCenter). Helping users navigate across multiple trusted prevention science platforms remains a translational need unmet by Blueprints’ and other online clearinghouses’ current conception, thereby addressing Gaps 2 and 3.

Third, AI software could provide guidance on research design, methods, analysis techniques, evaluation protocols, and strategies for translation to researchers partnering with community organizations and practitioners, grantees interested in satisfying evidence-based funding mandates, and consulting to policymakers. AI parameters could be embedded in Blueprints’ platform to explain criteria used to rate the evidence base of interventions and identify evidence gaps for Blueprints to consider. AI parameters could also identify interventions rated by Blueprints listed by different clearinghouses and explain how Blueprints’ ratings compare to others. In addition, AI can facilitate the inclusion of interventions described in the literature, including innovative and/or community-developed programs, that have yet to be subjected to rigorous evaluation with an RCT or QED. A process could be established for their review to denote their stage of development, and an indication of further evaluation research needed to meet Blueprints’ or other clearinghouse standards.

And fourth, once operational, a protocol would need to be established to ensure wide-scale awareness of Blueprints, familiarizing potential end-users with its utility, in effect, advancing the uptake of EBPIs. This activity would address Gap 6. It will also be important to end-users to provide information that is locally relevant (e.g., responsive to health surveillance data). A rigorous and well-tested marketing methodology for this protocol will determine resonance of messaging frameworks with different audiences for further refinement and targeting, and construction of an effective delivery vehicle.

**Discussion**

The primary advantage of an AI-delivered clearinghouse over approaches historically used by online clearinghouses is the ability to continually update and synthesize new and relevant evidence as it becomes available and provide stepwise, interactive search inquiries that are of greater utility to end-users. At all stages of navigation, weblinks would lead the user to external reference materials and databases and, when needed, will refer to experts or other users with relevant experience. For example, a user may require additional information on how to most effectively and cost-efficiently implement a particular program in their community, requiring more in-depth guidance and delineation of the pitfalls or barriers, along with recommended solutions. In effect, the search engine would provide for the type of interaction via AI software that might occur in a conversation, where one statement or query leads to a more personalized, informative and instructive response. With permission from a pool of experts, contact information could be provided to more intensively address concerns raised by users. And finally, for researchers partnering with end-users, there would be a searchable methodology section guidance on research design, methods, analysis techniques, evaluation protocols, and strategies for translation (i.e., replication and implementation).

This conception for an AI-driven clearinghouse would specifically fill each of the gaps identified in the Bridgespan Report (Neuhoff et al., 2015) as follows. (1) Comprehensiveness: Streamlining the systematic review process using machine learning that provides real-time data integration of current and extended evidence review items, thereby improving the timeliness, efficiency, and comprehensiveness of evidence synthesis and allowing for more responsive and effective solutions based on the latest knowledge and data. (2) Implementation: Providing community assessment and implementation support of well-tested operational protocols that ensure feasibility, acceptability, cultural relevance, and sustainability of EBPIs to end-users in any given community. (3) Guidance: Populating the clearinghouse website with AI-generated parameters needed to improve search functions by readily mapping the available EBPIs to existing needs, such as helping users select culturally sensitive EBPIs, making state-level funding decisions, or searching for samples of program evaluations reviewed to identify EBPIs that have validity with racially and ethnically diverse populations, and so forth.(4) Synthesis: Providing information particular policies and management systems needed to be in place for EBPIs to exert the greatest benefits, as well as synthesizing the evidence using nontechnical terms and descriptions of wise practices known to effectively target problems at hand.(5) Usability: Using understandable, concise, and unbiased information on EBPIs available on existing online clearinghouse websites that describes evaluation criteria and provides explanations of how ratings vary across clearinghouses. (6) Awareness: Substantially increasing the reach and salience of the information provided to a broader range of constituent groups via a large-scale outreach campaign as well as targeted marketing efforts directed toward specific end-users. These attributes are inherently built into an AI-driven clearinghouse and can be achieved with sufficient funding, as well as by calling upon the expertise of community organizers, policymakers, academics, evaluators, clearinghouse experts, federal government database keepers, implementation scientists, methodologists, computer scientists, and statisticians. And critical to this effort, to ensure its utility, input must be sought from all users (e.g., implementers of EBPIs, community groups, legislators, agencies, funders, potential beneficiaries) working in concert with researchers and experts on the clearinghouse team.

**Policy Benefits**

Incorporating AI into EBI clearinghouses will significantly benefit evidence-based policymaking by enabling our nation to more effectively deal with pressing prevention and public health policy questions, such as: (1) how to best educate and re-skill our young people to ensure successful futures; (2) what are wise practices to prevent violence in society, (3) how do we promote population-level mental and physical health, and (4) what strategies hold the most promise of uplifting the most vulnerable. Answers to these questions will be facilitated by using an AI-powered clearinghouse that builds on past efforts, is comprehensive, can be easily navigated, and is responsive to user needs. Platforms modeled after the one described herein can also be applied to other issue areas – e.g., health care, mental health and substance use treatment, environmental concerns, economic policies, and national security – to dramatically improve the effectiveness and efficiency of a wide range of government operations.

The AI-driven clearinghouse we propose would provide various constituent groups with the means to expeditiously and effectively make decisions that will benefit their work, outcomes of policies formulated, operations of government, and ultimately society as a whole. After initial outlays, money saved by implementing EBPIs shown to be impactful in reducing and preventing future problems can be used to support additional research needed to establish effects, track outcomes, support the clearinghouse, and fund more EBIs and/or reduce government deficits – which has potential to make for a stronger economy and more effective government operations.

In short, the data infrastructure with the features outlined herein will provide a comprehensive one-stop resource for information and assistance to deploy a range of evidence-based strategies for end-users. For example, researchers can readily access the available evidence, identify the gaps requiring further research, and continuously add to the database of effective interventions and policy options. Community members and organizations in need of guidance will be able to identify and implement wise practices. Policymakers at all levels of government can more readily determine what are the most effective interventions to fund (including interventions that reduce disparities), calling upon relevant existing federal databases to aid in decision-making. Agencies at all levels of government and community organizations can put into practice the most effective and cost-saving programs and policies available, utilizing relevant databases that are incorporated into the clearinghouse.

**Compliance with Ethical Standards**

**Funding** We did not receive support from any organization for the submitted work.

**Ethics approval** This study did not qualify as human subjects research.

**Conflicts of interest/Competing interests** One of the authors serves as a member of the Blueprints staff and has no financial or other conflict of interest with respect to any of the concepts discussed in this article.

**Consent to participate** Not applicable.

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