American Journal of Preventive Cardiology xxx (xxxx) xxx

Contents lists available at ScienceDirect

American Journal of Preventive Cardiology

journal homepage: www.journals.elsevier.com/american-journal-of-preventive-cardiology

Commentary

Reducing hypertension disparities: The potential role of patient-facing large language models

Farah Allouch [a,b], Saad Hassan [c], Flor Alvarado [b], Syeda Mah Noor Asad [c], Dee Parekh [d], Renata Johnson [a], Marilyn Payne [e], David Gardner [d], Nicholas Mattei [b], Keith C Ferdinand [b,*]

[a] Department of Epidemiology, Celia Scott Weatherhead School of Public Health and Tropical Medicine, Tulane University, New Orleans, LA, United States
[b] Department of Medicine, School of Medicine, Tulane University, New Orleans, LA, United States
[c] Department of Computer Science, School of Science and Engineering, Tulane University, New Orleans, LA, United States
[d] A.B. Freeman School of Business, Tulane University, New Orleans, LA, United States
[e] Payne & Associates Counseling & Consulting Services, New Orleans, LA, United States

ABSTRACT

Hypertension disparities persist despite effective lifestyle and pharmacological therapies, underscoring the need for strategies that deliver evidence-based care more equitably. This commentary examines the potential for patient-facing large language model-based systems to reduce hypertension disparities and proposes an implementation science approach to their development, integration, and evaluation. These systems could expand access to personalized health education, behavioral support, care navigation, and clinical escalation between traditional care encounters. However, biased training data, inaccurate or overly agreeable responses, unequal digital access and literacy, and mistrust of automated systems could reinforce existing inequities. Technical safeguards are necessary but insufficient. Equitable implementation should begin with meaningful community engagement and human-centered co-design, incorporate trusted knowledge sources and human oversight, complement team-based care, and iteratively address local barriers and facilitators. Evaluation should assess both clinical effectiveness and implementation outcomes, including reach, adoption, acceptability, feasibility, cost, sustainability, and equitable distribution of benefits. Patient-facing large language model systems should augment rather than replace established care models. Their value will depend not only on technical capabilities, but on whether they safely, sustainably, and equitably extend evidence-based hypertension care in real-world settings.

1. Introduction

Hypertension is the leading preventable risk factor for premature death and disability worldwide [1], accounting for approximately 10.8 million cardiovascular disease deaths and 209 million disability-adjusted life years [2]. Despite the availability of safe and effective lifestyle and pharmaceutical therapies, substantial disparities in hypertension care and control persist across race, income, and geography in the United States (U.S.) [3–5]. For example, Black patients are initiated on antihypertensive therapy at higher systolic blood pressure (BP) levels (136.0 mmHg versus 130.9 mmHg) and are less likely to receive guideline-recommended medications (60.5% versus 73.8%) compared with White patients [4]. Similarly, compared to patients with higher incomes, those with lower incomes had lower rates of hypertension awareness (54.6% versus 60.5%) and control (81.7% versus 85.8%) [5]. Reducing these persistent inequities in hypertension care is essential to improving cardiovascular health and achieving meaningful gains in population health.

Achieving equitable hypertension control remains limited by barriers at multiple levels [6,7]. At the patient level, adverse social determinants of health, including poor housing environments, food insecurity, and psychosocial stressors, influence patients' ability to access healthy foods, engage in safe physical activity, and access hypertension care. At the clinician level, insufficient time for lifestyle counseling and nonadherence to clinical guidelines impede evidence-based care. At the heath system level, fragmented care and lack of reimbursement for preventive services further contribute to inequitable hypertension control. Thus, achieving population-level hypertension control is limited not by a lack of evidence-based interventions, but by our ability to deliver them effectively, consistently, and equitably.

Team-based care led by physicians, pharmacists, or community health workers (CHWs), is an evidence-based strategy that addresses many of the barriers to hypertension control [8]. In particular, CHWs play a critical role in delivering culturally tailored, relationship-based hypertension interventions outside of traditional healthcare settings

* Corresponding author at: Gerald S. Berenson Endowed Chair in Preventative Cardiology, Professor of Medicine, Tulane University School of Medicine, 1430 Tulane Avenue, Mail Code #8048, New Orleans, LA, 70112, United States.
E-mail address: kferdina@tulane.edu (K.C. Ferdinand).

https://doi.org/10.1016/j.ajpc.2026.101813
Received 7 August 2026; Received in revised form 31 August 2026; Accepted 4 September 2026
Available online 5 September 2026
2666-6677/

Please cite this article as: Farah Allouch et al., *American Journal of Preventive Cardiology*, https://doi.org/10.1016/j.ajpc.2026.101813

[9–11]. However, team-based care remains resource intensive, with limitations in workforce capacity, training, and reimbursement that constrain its scalability and long-term sustainability [12].

Recent advances in generative artificial intelligence (AI) may present unprecedented opportunities to improve hypertension control [13–16]. Large language models (LLMs) are generative AI systems trained on large volumes of text and increasingly, multimodal data such as images and audio. These systems can understand and generate human-like language as well as simplify and contextualize complex information from multiple sources [17].

Patient-facing LLM-based systems, in which patients interact directly with LLMs independently or as part of clinician- or team-based care, are a promising avenue to deliver personalized education, lifestyle counseling, and treatment support at scale. Such systems can extend support outside of traditional care settings without increasing clinician burden [15,18–20]. To date, much of the discussion surrounding healthcare applications of LLMs has focused on technical performance, safety, and ethical considerations, with comparatively less attention devoted to the equitable development and implementation of LLM-enabled interventions. Technical performance is essential but, on its own, cannot ensure that these interventions are effective in real-world settings and improve health equity. Further, without meaningful engagement of communities disproportionately affected by hypertension throughout the development and implementation process, patient-facing LLM-based systems risk exacerbating rather than reducing existing disparities.

This commentary examines the potential role of patient-facing LLM-based systems in reducing hypertension disparities and presents an implementation science perspective for the equitable development, integration, and evaluation of patient-facing LLM-based hypertension interventions.

2. Patient-facing LLM-based systems: A new opportunity for hypertension control

LLM-based systems are applications are systems that use an LLM as a core component, often combined with additional tools, data sources, and safeguards tailored to a specific health-related purpose. These systems have many promising applications in healthcare, which have been reviewed elsewhere [13–16,20]. Relevant to hypertension, LLM-based systems have the potential to improve prevention, treatment, and long-term BP control [15,16,21]. Although these models have applications for both clinicians and patients, patient-facing LLM-based systems have unique potential to expand access to evidence-based hypertension support beyond traditional healthcare settings. These systems could be used as a standalone tool or be integrated into clinician- or team-based care with human oversight. This commentary focuses primarily on integrated applications, in which patient-facing LLM-based systems augment rather than replace human-delivered care.

Broadly, patient-facing LLM-based systems have focused on four functions: (1) care navigation, (2) health education, (3) behavioral support, and (4) clinical escalation (Table 1). Patient-facing LLM-based systems can facilitate navigation by helping patients understand discharge instructions, prepare for clinic visits, and connect with appropriate healthcare and community resources [22]. They can also provide interactive, personalized education tailored to patients' language, literacy, and cultural context, while reinforcing guideline-based recommendations [14,19]. For example, LLM-based systems could instruct patients on best practices for home BP measurement, explain common medication side effects, and describe the consequences of suboptimal risk factor control.

Beyond education, these LLM-based systems have the potential to support sustained behavior change through motivational interviewing, goal setting, and personalized feedback to encourage medication adherence, healthy dietary patterns including DASH-patterned (Dietary Approaches to Stop Hypertension) diets and low-sodium food substitutions, and regular physical activity [23,24]. Finally, these systems can identify emergency symptoms, including those related to hypertensive crises and suicidal ideation, and facilitate escalation to appropriate clinical care. Collectively, these capabilities represent a shift from episodic hypertension care delivered during clinic visits toward continuous support that extends hypertension management into patients' daily lives.

Table 1
Barriers to hypertension control addressed by patient-facing large language models.

Barriers to hypertension control	Potential role of patient-facing LLMs
Inconsistent delivery of evidence-based care	Standardize and extend the delivery of guideline-concordant hypertension education and behavioral support
Limited accessibility to care	Provides ongoing support without need for transportation
Fragmented care	Maintains continuity between visits
Insufficient time for lifestyle counseling	Extends counseling beyond brief office visits
Poor medication adherence	Provides ongoing reminders, motivation, and problem-solving
Limited health literacy	Tailors hypertension education to appropriate levels
Poor care navigation	Supports navigation to healthcare and community resources

3. Will patient-facing LLM-based systems reduce or exacerbate hypertension disparities?

Several technical challenges may limit the equitable use of patient-facing LLM-based systems in hypertension care. Given that these systems are trained on real-world data that reflect existing societal inequities, patient-facing LLM-based systems may inadvertently amplify those inequities [25,26]. These concerns have been demonstrated across healthcare AI more broadly. For example, Obermeyer et al. found that an algorithm widely used by U.S. health systems failed to identify more than half of Black patients in need of additional care [26]. Similarly, LLM-based systems may generate inaccurate responses ("hallucinations") or affirm users' inaccurate beliefs ("sycophancy"), potentially undermining patient safety and trust [13,27,28]. In addition, disparities in digital literacy and access as well as broadband limitations and mistrust of automated systems may prevent the benefits of LLM-based systems being equitably distributed across the population.

Several approaches may mitigate these risks. For example, safeguards must be implemented to clearly define the boundaries of responses from LLM-based systems, with clinical diagnoses and medication management decisions deferred to qualified clinicians. Technical approaches such as retrieval-augmented generation (RAG) have been shown to reduce hallucinations in LLM-based systems [14,29]. RAG grounds the system's responses in trusted knowledge bases, which may also improve user trust [14]. Working with end-users to design and shape the functionality of LLM-based systems, while providing tools to increase digital literacy and overcome broadband limitations, may also help distribute the benefits of these systems to those who stand to benefit most.

However, addressing technical limitations alone is unlikely to ensure that patient-facing LLM-based systems reduce, rather than exacerbate, hypertension disparities. The larger challenge is ensuring that patient-facing LLM-based systems are designed around the needs, preferences, and lived experiences of the communities they are intended to serve.

4. Framing patient-facing LLM-based systems through an implementation science lens

Implementation science is the systematic study of methods to promote the adoption, integration, and sustainment of evidence-based interventions in real-world settings [30,31]. Whereas efficacy research asks whether an intervention works under ideal conditions, implementation science seeks to understand how effective interventions can be successfully integrated into routine practice to maximize population health impact. In hypertension, the evidence-based interventions are already well established and include lifestyle modification and pharmaceutical interventions [32]. The challenge is no longer identifying what works, but determining how to deliver these interventions effectively, equitably, and sustainably. From this perspective, patient-facing LLM-based systems represent not a new intervention, but a promising implementation strategy for delivering evidence-based hypertension care beyond traditional clinical encounters.

An implementation science perspective fundamentally changes the development process for patient-facing LLM-based systems (Fig. 1). Rather than beginning with model development, implementation science starts by engaging communities to understand local priorities, needs, and contextual factors that influence implementation. These insights guide the co-development of the AI-enabled intervention and its implementation strategies, including the features and capabilities of the patient-facing LLM and future integration with traditional team-based care approaches.

Differences in culture, language, resources, and lived experience can substantially influence how interventions are adopted and sustained, highlighting the importance of meaningful community engagement in implementation projects targeted towards health equity [33]. Community engagement emphasizes engaging a wide range of stakeholders in the implementation process, including policymakers, clinicians, community organizations, and other community members with expertise regarding local context that may affect the implementation process [34, 35]. Ideally, community representatives should be members of the target population and included as partners in intervention and implementation design and decision-making.

To operationalize this approach, implementation scientists use theories, models, and frameworks to identify barriers and facilitators of

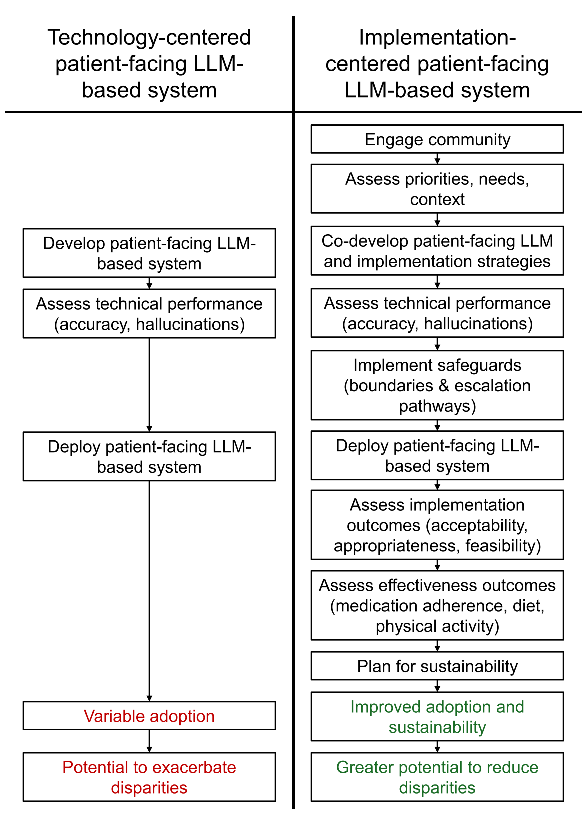

Fig. 1. Technology- versus implementation-centered development of patient-facing large language model-based systems for hypertension.

implementation, select evidence-based implementation strategies, and provide a blueprint for implementation and evaluation [36]. Several process frameworks have been proposed to guide the implementation digital interventions, including the Integrate, Design, Assess, and Share (IDEAS) and the Discover, Design/Build, and Test (DDBT) framework developed by colleagues at the University of Washington [37]. The DDBT framework may be especially useful for the equitable implementation of patient-facing LLM-based systems as it emphasizes an iterative, stakeholder-informed development grounded in human-centered design, which centers the needs and experiences of intended users throughout development [38].

Following development and deployment, patient-facing LLM-based systems should undergo rigorous evaluation of both implementation and effectiveness outcomes. Hybrid effectiveness-implementation designs may be particularly useful for simultaneously assessing these outcomes in real-world settings. Implementation outcomes may be guided by established evaluation frameworks, such as Reach, Efficacy, Adoption, Implementation, Maintenance (RE-AIM) or Proctor's implementation outcomes, including acceptability, appropriateness, feasibility, and cost. Effectiveness outcomes, including behavioral (e.g., minutes of physical activity per week, diet scores) and metabolic outcomes (e.g., blood pressure and cholesterol levels), should also be assessed to establish clinical relevance. Finally, post-deployment monitoring and planning for long-term sustainability are essential to ensure that the benefits are maintained and equitably distributed.

5. Conclusion and future directions

Hypertension disparities persist despite decades of effective therapies, highlighting the need for strategies that improve the equitable delivery of evidence-based care. Patient-facing LLM-based systems should not replace evidence-based models of care, such as team-based care, but may complement and extend their reach by providing education, behavioral support, and care navigation between in-person encounters, while facilitating escalation to appropriate clinical care, as appropriate. A research agenda for these systems should progress from usability and safety testing in target communities to pilot implementation in clinical and community settings, hybrid effectiveness-implementation trials, and post-deployment monitoring. Framing patient-facing LLM-based systems as implementation strategies shifts the focus from what these tools can do to whether they can equitably extend evidence-based hypertension care and reduce disparities in real-world settings.

Statement of author contributions

All co-authors contributed to the conception and design of the study. FA drafted the article and all other co-authors revised it critically for important intellectual content and provided final approval of the version to be submitted.

Sources of funding

Investigators on this commentary were supported by several National Institutes of Health awards, including P20GM109036, UH3HL151309, and R01MD018193. The content is solely the responsibility of the authors and does not necessarily represent the official views the National Institutes of Health.

CRediT authorship contribution statement

Farah Allouch: Writing – original draft, Conceptualization. **Saad Hassan:** Writing – review & editing, Conceptualization. **Flor Alvarado:** Writing – review & editing, Conceptualization. **Syeda Mah Noor Asad:** Writing – review & editing, Conceptualization. **Dee Parekh:** Writing – review & editing, Conceptualization. **Renata Johnson:** Writing –

review & editing, Conceptualization. **Marilyn Payne:** Writing – review & editing, Conceptualization. **David Gardner:** Writing – review & editing, Conceptualization. **Nicholas Mattei:** Writing – review & editing, Conceptualization. **Keith C Ferdinand:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Keith C. Ferdinand reports a relationship with National Institutes of Health that includes: funding grants. Keith C. Ferdinand reports a relationship with Novartis that includes: consulting or advisory. Keith C. Ferdinand reports a relationship with Medtronic that includes: consulting or advisory. Keith C. Ferdinand reports a relationship with Eli Lilly that includes: consulting or advisory. Keith C. Ferdinand reports a relationship with Boehringer Ingelheim Corp USA that includes: consulting or advisory. Keith C. Ferdinand reports a relationship with Janssen Inc that includes: consulting or advisory. Farah Allouch reports a relationship with National Institutes of Health that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Palaniappan LP, Allen NB, Almarzooq ZI, et al. 2026 Heart disease and stroke statistics: a report of US and global data from the American heart association. Circulation 2026;153(9):e275-e906. https://doi.org/10.1161/cir.0000000000001412.
[2] Vaduganathan M, Mensah GA, Turco JV, Fuster V, Roth GA. The global burden of cardiovascular diseases and risk: a compass for future health. J Am Coll Cardiol 2022;80(25):2361–71. https://doi.org/10.1016/j.jacc.2022.11.005.
[3] O'Connell SS, Whelton PK, Li F, et al. Global Hypertension 2000 to 2020: trends, disparities, and progress in awareness, treatment, and control. J Am Coll Cardiol 2026;87(18):2338–51. https://doi.org/10.1016/j.jacc.2025.12.091.
[4] Goleva SB, Williams A, Schlueter DJ, et al. Racial and ethnic disparities in antihypertensive medication prescribing patterns and effectiveness. Clin Pharmacol Ther 2024;116(6):1544–53. https://doi.org/10.1002/cpt.3360.
[5] Richardson LC, Vaughan AS, Wright JS, Coronado F. Examining the hypertension control cascade in adults with uncontrolled hypertension in the US. JAMA Network Open 2024;7(9):e2431997-e2431997. https://doi.org/10.1001/jamanetworkopen.2024.31997.
[6] Health BoP, Reduce CoPHPt, Population CHitU. A population-based policy and systems change approach to prevent and control hypertension. National Academies Press; 2010.
[7] Khatib R, Schwalm JD, Yusuf S, et al. Patient and healthcare provider barriers to hypertension awareness, treatment and follow up: a systematic review and meta-analysis of qualitative and quantitative studies. PLoS One 2014;9(1):e84238. https://doi.org/10.1371/journal.pone.0084238.
[8] Mills KT, Obst KM, Shen W, et al. Comparative effectiveness of implementation strategies for blood pressure control in hypertensive patients: a systematic review and meta-analysis. Ann Intern Med 2018;168(2):110–20. https://doi.org/10.7326/m17-1805.
[9] Jafar TH, Gandhi M, HAd Silva, et al. A community-based intervention for managing hypertension in rural South Asia. New Engl J Med 2020;382(8):717–26. https://doi.org/10.1056/NEJMoa1911965.
[10] He J, Ouyang N, Guo X, et al. Effectiveness of a non-physician community health-care provider-led intensive blood pressure intervention versus usual care on cardiovascular disease (CRHCP): an open-label, blinded-endpoint, cluster-randomised trial. Lancet 2023;401(10380):928–38. https://doi.org/10.1016/s0140-6736(22)02603-4.
[11] Sun Y, Mu J, Wang DW, et al. A village doctor-led multifaceted intervention for blood pressure control in rural China: an open, cluster randomised trial. Lancet 2022;399(10339):1964–75. https://doi.org/10.1016/S0140-6736(22)00325-7.
[12] Schriger SH, Knowles M, Daglieri T, Kangovi S, Beidas RS. Barriers and facilitators to implementing an evidence-based community health worker model. JAMA Health Forum 2024;5(3):e240034. https://doi.org/10.1001/jamahealthforum.2024.0034.
[13] Bharel M, Auerbach J, Nguyen V, DeSalvo KB. Transforming public health practice with generative artificial intelligence. Health Aff 2024;43(6):776–82. https://doi.org/10.1377/hlthaff.2024.00050.
[14] Yang R, Ning Y, Keppo E, et al. Retrieval-augmented generation for generative artificial intelligence in health care. Npj. Health Systems 2025;2(1):2. https://doi.org/10.1038/s44401-024-00004-1.
[15] Armoundas AA, Narayan SM, Arnett DK, et al. Use of artificial intelligence in improving outcomes in Heart disease: a scientific statement from the American heart association. Circulation 2024;149(14):e1028-e1050. https://doi.org/10.1161/CIR.0000000000001201.
[16] Meder B, Asselbergs FW, Ashley E. Artificial intelligence to improve cardiovascular population health. Eur Heart J 2025;46(20):1907–16. https://doi.org/10.1093/eurheartj/ehaf125.
[17] Russell SJ. Artificial intelligence a modern approach. Pearson Education, Inc.; 2010.
[18] Castro O, Mair JL, Salamanca-Sanabria A, et al. Development of "LvL UP 1.0": a smartphone-based, conversational agent-delivered holistic lifestyle intervention for the prevention of non-communicable diseases and common mental disorders. Front Digit Health 2023;5:1039171. https://doi.org/10.3389/fdgth.2023.1039171.
[19] Kim DD, Zhang J, Sagae K, et al. Human-delivered conversation versus AI chatbot conversation in increasing heart attack knowledge in women in the United States: quasi-experimental studies. J Med Internet Res 2025;27:e73184. https://doi.org/10.2196/73184.
[20] Reddy S. Generative AI in healthcare: an implementation science informed translational path on application, integration and governance. Implement Sci 2024;19(1):27. https://doi.org/10.1186/s13012-024-01357-9.
[21] Shimbo D, Shah RU, Abdalla M, et al. Transforming hypertension diagnosis and management in the era of artificial intelligence: a 2023 National Heart, Lung, and Blood Institute (NHLBI) workshop report. Hypertension 2025;82(1):36–45. https://doi.org/10.1161/hypertensionaha.124.22095.
[22] Kocaballi AB, Ijaz K, Laranjo L, et al. Envisioning an artificial intelligence documentation assistant for future primary care consultations: a co-design study with general practitioners. J Am Med Inform Assoc 2020;27(11):1695–704. https://doi.org/10.1093/jamia/ocaa131.
[23] Oh YJ, Zhang J, Fang ML, Fukuoka Y. A systematic review of artificial intelligence chatbots for promoting physical activity, healthy diet, and weight loss. Int J Behav Nutr Phys Act 2021;18(1):160. https://doi.org/10.1186/s12966-021-01224-6.
[24] Aggarwal A, Tam CC, Wu D, Li X, Qiao S. Artificial intelligence–Based chatbots for promoting health behavioral changes: systematic review. J Med Internet Res 2023;25:e40789. https://doi.org/10.2196/40789 (Review).
[25] Omar M, Soffer S, Agbareia R, et al. Sociodemographic biases in medical decision making by large language models. Nat Med 2025;31(6):1873–81. https://doi.org/10.1038/s41591-025-03626-6.
[26] Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science 2019;366(6464):447–53. https://doi.org/10.1126/science.aax2342.
[27] Ji Z, Lee N, Frieske R, et al. Survey of hallucination in natural language generation. ACM Comput Surv 2023;55(12):248. https://doi.org/10.1145/3571730. Article.
[28] Malmqvist L. Sycophancy in large language models: causes and mitigations. URL, https://arxiv.org/abs/241115287; 2024.
[29] Shuster K, Poff S, Chen M, Kiela D, Weston J. Retrieval augmentation reduces hallucination in conversation. Findings of the Association for Computational Linguistics. EMNLP 2021;2021:3784–803.
[30] Bauer MS, Damschroder L, Hagedorn H, Smith J, Kilbourne AM. An introduction to implementation science for the non-specialist. BMC Psychol 2015;3(1):32. https://doi.org/10.1186/s40359-015-0089-9.
[31] Koh S, Lee M, Brotzman LE, Shelton RC. An orientation for new researchers to key domains, processes, and resources in implementation science. Transl Behav Med 2020;10(1):179–85. https://doi.org/10.1093/tbm/iby095.
[32] Arnett DK, Blumenthal RS, Albert MA, et al. 2019 ACC/AHA guideline on the primary prevention of cardiovascular disease: a report of the American college of Cardiology/American heart association task force on clinical practice guidelines. Circulation 2019;140(11):e596-e646. https://doi.org/10.1161/CIR.0000000000000678.
[33] Fagan HB, Ortiz J, Riveros BT. Why CEnR matters for health equity. Dela J Public Health 2018;4(5):4–7. https://doi.org/10.32481/djph.2018.11.002.
[34] Springgate BF, Sugarman O, Wells KB, et al. Community partnered participatory research in Southeast Louisiana communities threatened by climate change: the C-learn experience. Am J Bioeth 2021;21(10):46–8. https://doi.org/10.1080/15265161.2021.1965248.
[35] Epps F, Gore J, Flatt JD, et al. Synthesizing best practices to promote health equity for older adults through community-engaged research. Res Gerontol Nurs 2024;17(1):9–16. https://doi.org/10.3928/19404921-20231205-01.
[36] Nilsen P. Making sense of implementation theories, models, and frameworks. Implement Sci 2020;3.0:53–79.
[37] Mummah SA, Robinson TN, King AC, Gardner CD, Sutton S. IDEAS (Integrate, design, assess, and share): a framework and toolkit of strategies for the development of more effective digital interventions to change health behavior. J Med Internet Res 2016;18(12):e317. https://doi.org/10.2196/jmir.5927.
[38] Giacomin J. What is human centred design? Design J 2014;17(4):606–23. https://doi.org/10.2752/175630614×14056185480186.