COMMENTARY

Delivering on the Promise of Technology to Augment Behavioral Interventions in Type 2 Diabetes

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Individuals with type 2 diabetes face a myriad of daily self-management decisions, encompassing diet, exercise, medication, and glucose monitoring. These behaviors influence outcomes such as hemoglobin A_{1c} (HbA_{1c}) and body weight, which in turn drive longer-term complications. Accordingly, enhanced support for positive self-care behaviors is a priority to promote health and well-being in the context of type 2 diabetes.

Following a healthful diet is particularly central to type 2 diabetes self-care (1), yet accurately measuring and changing diet-related behaviors remains notoriously difficult. Emerging technologies, including diet-tracking apps, software, and sensors (2,3), offer opportunities to more accurately monitor and improve dietary aspects of type 2 diabetes self-care, particularly when combined with information from fitness trackers, wearables, and continuous glucose monitors. However, it remains unclear how best to integrate and use these data sources while minimizing the patient burden and bias that commonly plagues studies in real-world settings.

For this reason, the study by Lee et al. (4) in this issue of *Diabetes Care* represents an exciting addition to the behavioral intervention literature on type 2 diabetes. The study assessed a digital health care platform that incorporated data from a Bluetooth-integrated glucose meter, blood pressure cuff, scale, accelerometer, and artificial intelligence (AI)-based food recognition program to which participants uploaded photographs (5). Investigators randomized Korean adults with elevated BMI and type 2 diabetes (n = 294) into three groups: usual-care control (group A); usual care plus access to the digital platform with no monitoring or support (group B); and usual care with training on digital platform use, remote text messaging feedback from medical staff prompted by participant data, and intermittent continuous glucose monitor use (group C). Relative to usual care, groups B and C showed modest improvements in HbA_{1c} and other outcomes at 48 weeks. Utilization of the digital platform and reductions in HbA_{1c} were greatest in group C.

Study strengths include use of AI-based food recognition technology, integration of multisource data, a large sample, and a 48-week follow-up period. A key limitation relates to the complex, multicomponent nature of the group C intervention, which convolutes the understanding of the mechanisms by which it reduced HbA_{1c} and body weight. Specifically, the contribution of the AI-based food recognition technology is unclear. While the improvements in outcomes observed in group B may be reasonably attributed to this technology, the numerous additional group C components make it difficult to assess both the independent contribution of AI-based food recognition software and the ways in which it was augmented by the other intervention components. Moreover, diet is an important factor for weight and glycemic control, but it is unclear how the personalized text messages targeted these outcomes. Other limitations include uncertain generalizability to other countries and to patients with less optimal baseline glycemic management.

All told, one of the greatest contributions of the study by Lee et al. (4) is the proof of concept it demonstrates for technology-augmented behavioral interventions in type 2 diabetes. The authors *1*) integrated data from an innovative, AI-based food recognition software into a digital health care platform, alongside other biometric data, and *2*) feasibly and acceptably delivered a technology-augmented behavioral intervention to individuals with type 2 diabetes. The study thus underscores the promise of technology for reducing the burden of diet tracking, facilitating personalized feedback, and promoting more effective diabetes self-management.

As available data sources proliferate and the potential settings for technology-based behavioral interventions expand, this emerging field where technology, behavioral science, and clinical diabetes care interface is at an opportune stage

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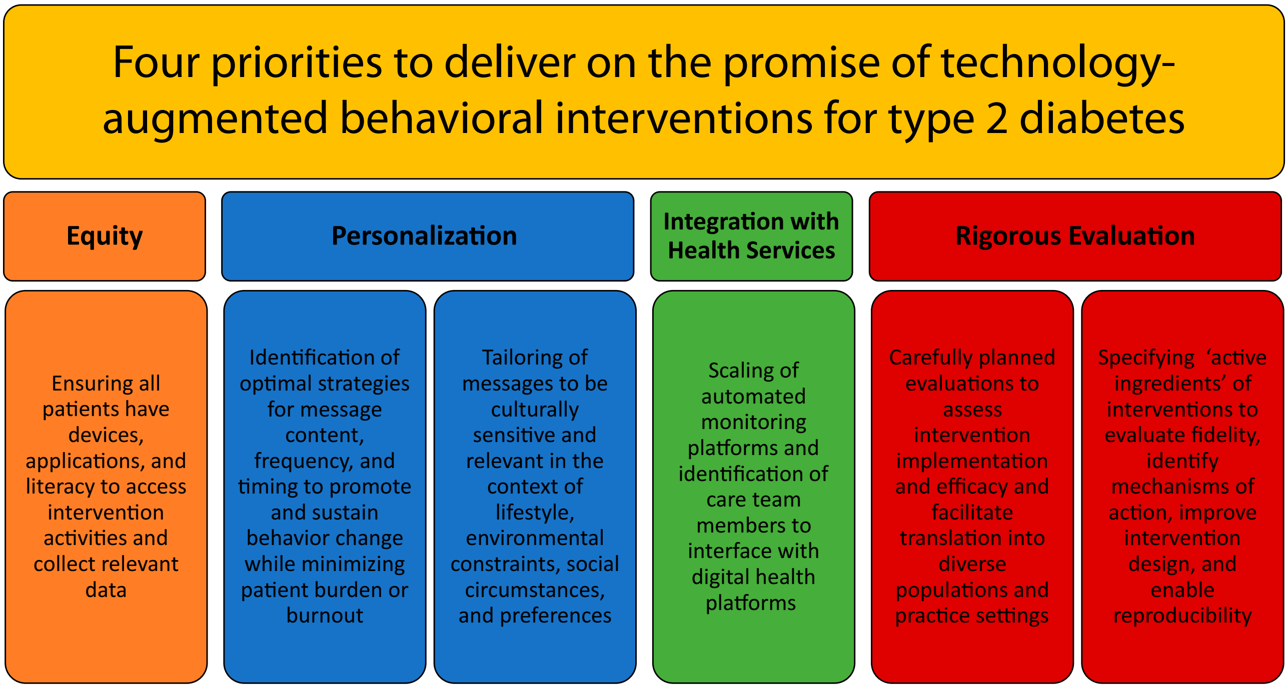

Figure 1—Priorities to deliver on the promise of technology-augmented behavioral interventions for type 2 diabetes.

for exploring priorities and defining new standards to promote equitable, patient-centered, and rigorous innovation. We propose four priorities to help assure future research delivers on the promises of technology-augmented behavioral interventions for type 2 diabetes (Fig. 1).

The first priority is equity, which focuses on barriers to accessing technology-augmented behavioral interventions and their associated tools. Participants in the study by Lee et al. (4) used personal mobile devices. Smartphone use in South Korea was reported at 95% (4). In settings with lower smartphone ownership, such as the U.S., where ownership is 85% overall, 61% in adults ≥65 years (6), and varies with socioeconomic position, ensuring equity in intervention utilization and outcomes is more complex. Challenges may include variable connectivity for data transmission and disparate levels of technological and health literacy.

The second priority is personalization. In the study by Lee et al. (4), group C participants received text messages from four categories that were triggered by adherence to investigator-specified behavioral targets. As diabetes care moves toward an integrated model of "precision monitoring," or multimodal assessment of glucose, behaviors, diet, sleep, and other stressors (7), personalization strategies may incorporate passively collected information from mobile phone applications, sensors, and wearables, along with actively collected information from surveys or ecological momentary assessments. More research is needed to optimally balance the advantages of personalization with the burden of data collection. Research is also needed to identify effective message strategies for replication in future studies, which requires evaluating associations between the content, frequency, and timing of feedback and desired behavioral or health responses. Finally, research should underpin behavioral prompts and other intervention strategies to maximize cultural sensitivity and relevance to individuals' environmental constraints (e.g., food access), social circumstances (e.g., living situation), and other values or preferences.

The third priority focuses on integration with health services. If interest in digital health platforms and AI-based technology continues to expand, it will be critical to design interventions that integrate with available health system information technology, leverage existing clinical staff for intervention delivery, and preserve patient privacy. Automated monitoring and machine learning analytics may help stratify patients according to health status and trends, directing limited professional resources to those patients most urgently needing support.

The fourth priority supports the first three: rigorous evaluation. Guidelines highlight the importance of building data collection processes into intervention studies to facilitate assessment of how the intervention achieves its outcomes, how the intervention may be iterated to improve efficacy, equity, and implementation, and how to adapt the intervention for different clinical contexts (8–10). At the outset, developing a logic model for the different components of complex technology-based interventions and their intended effects can ensure collection of appropriate metrics for these goals. Data relevant to future clinical implementation of the intervention should be gathered throughout intervention development, even during the traditional efficacy testing phase. This goal can be accomplished with guidance from frameworks like RE-AIM (Reach, Effectiveness, Adoption, Implementation, and Maintenance) and PRISM (Practical, Robust Implementation and Sustainability Model) (11,12).

Rigorous evaluation processes are especially important for behavioral interventions with multiple components, such as those for group C in the study by Lee et al. (5). To analyze such interventions, the behavior change technique taxonomy offers a standardized set of terms to granularly characterize the active ingredients of an intervention (13). Coding intervention activities through this taxonomy facilitates understanding of associations between intervention components, participant behaviors and outcomes, the intervention's mechanisms of action, dose and fidelity, requirements for intervention refinement, and replication strategies. A complementary approach is the Multiphase Optimization Strategy (MOST) study design, which uses efficient experiments to evaluate intervention components' individual and combined effects, thus clarifying which doses of each component and combinations thereof produce the best outcomes (14).

Technology-augmented diabetes care has a bright future, and the study by Lee et al. (4) provides a glimpse into how innovative new technologies can be integrated into a practical, acceptable, and efficacious intervention for type 2 diabetes. It prompts us to imagine a future in which dietary data are collected through AI-based software with minimal burden and bias, providing the basis for truly data-driven behavioral support that honors the complexity of day-to-day management activities and supports patients in achieving their best possible outcomes.

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