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From Carbohydrate Counting to Artificial Intelligence:

Redefining the Model of Diabetes Care

Teaching patients to count carbohydrates has been one of the main educational tools in the nutritional treatment of diabetes. This strategy seeks to provide patients with the autonomy to adjust insulin doses according to what they eat. In theory, it is an effective method to improve glycemic control in individuals who are insulin-dependent. In practice, however, it is not so simple.

Counting carbohydrates requires more than theoretical knowledge; it demands careful observation of plates, precise interpretation of portions, and nearly automatic calculations before every meal. This also requires sustained attention, mental agility, and perseverance. The problem is that consistency does not always align with real life. Despite reinforcement from health professionals, various studies show that adherence often declines steeply after only a few months, largely because of the burden of maintaining such a demanding routine long term.

In reality, few people weigh foods or check nutrition labels every time they eat. Only 1 in 3 individuals with type 1 diabetes mellitus reports calculating carbohydrate servings before meals, and most often this calculation is performed "by eye," which inevitably introduces errors. Studies have shown that more than 60% of meals assessed by people with type 1 diabetes mellitus are underestimated for carbohydrate content, with a mean deviation of approximately 15 g per meal. This discrepancy is not trivial; it may account for up to 13% of the time patients spend in hyperglycemia. For perspective, even a 5% change in time in range is considered clinically relevant in terms of control and complication prevention.

In this context, artificial intelligence (AI) has entered the field of nutrition. What once required weighing foods and consulting tables can now be achieved with a single action: a mobile phone photograph. But the real potential is not only in automating tasks. The shift lies in moving away from the notion that people with diabetes must behave like highly trained "calculating machines" and toward understanding them as individuals who need continuous and realistic support. AI offers this leap. It allows us to envision a model where technology not only counts but also understands context, habits, and personal needs. A model that evolves from calculation to intelligent support, from estimation to anticipation, from generalization to personalization.

Due to advances in computer vision and machine learning, applications already exist that can identify foods on a plate, estimate portion sizes, and calculate macronutrients automatically. This immediate analytical capacity represents a paradigm shift for many patients with diabetes, who until now had to rely almost entirely on their own perception.

The main appeal of these solutions lies in their accessibility and ease of use, as well as their potential to reduce errors and improve decision-making precisely when it matters—before eating. Studies have shown that automated nutrition estimation from images often outperforms the perception of average patients and, in some cases, even surpasses health professionals under uncontrolled conditions. Notably, even using a widely available solution such as ChatGPT (OpenAI) for this task has produced encouraging results, with error margins < 10%.

AUGMENTED EDUCATION: A NEW WAY OF TEACHING DIABETES SELF-MANAGEMENT

Another domain where AI may transform diabetes care is education. Until now, most nutrition education has relied on traditional approaches: lectures, pamphlets, exchange tables, and theoretical examples. While useful, these methods have a structural limitation: education occurs outside the context in which patients make real-world decisions.

With the integration of tools such as computer vision, voice assistants, and machine learning, it is possible to create learning scenarios at the very moment and place where eating occurs. For example, a Moroccan mother could scan a plate of lentils and instantly receive an audio explanation in her native language regarding carbohydrate content, balance, and the appropriate portion for her 8-year-old child recently diagnosed with type 1 diabetes. No formulas, no labels, no barriers.

This new model does more than transmit information—it contextualizes and adapts it, making it relevant. An adolescent with poor adherence might engage with an app presenting challenges based on images of real meals from their environment. An older patient with type 2 diabetes mellitus who struggles with digital menus might receive daily visual reminders with simple portion adjustments, without needing to type.

The innovation lies not in the technology itself but in its ability to transform each meal into a learning opportunity without relying on memory or discipline. The aim is to »

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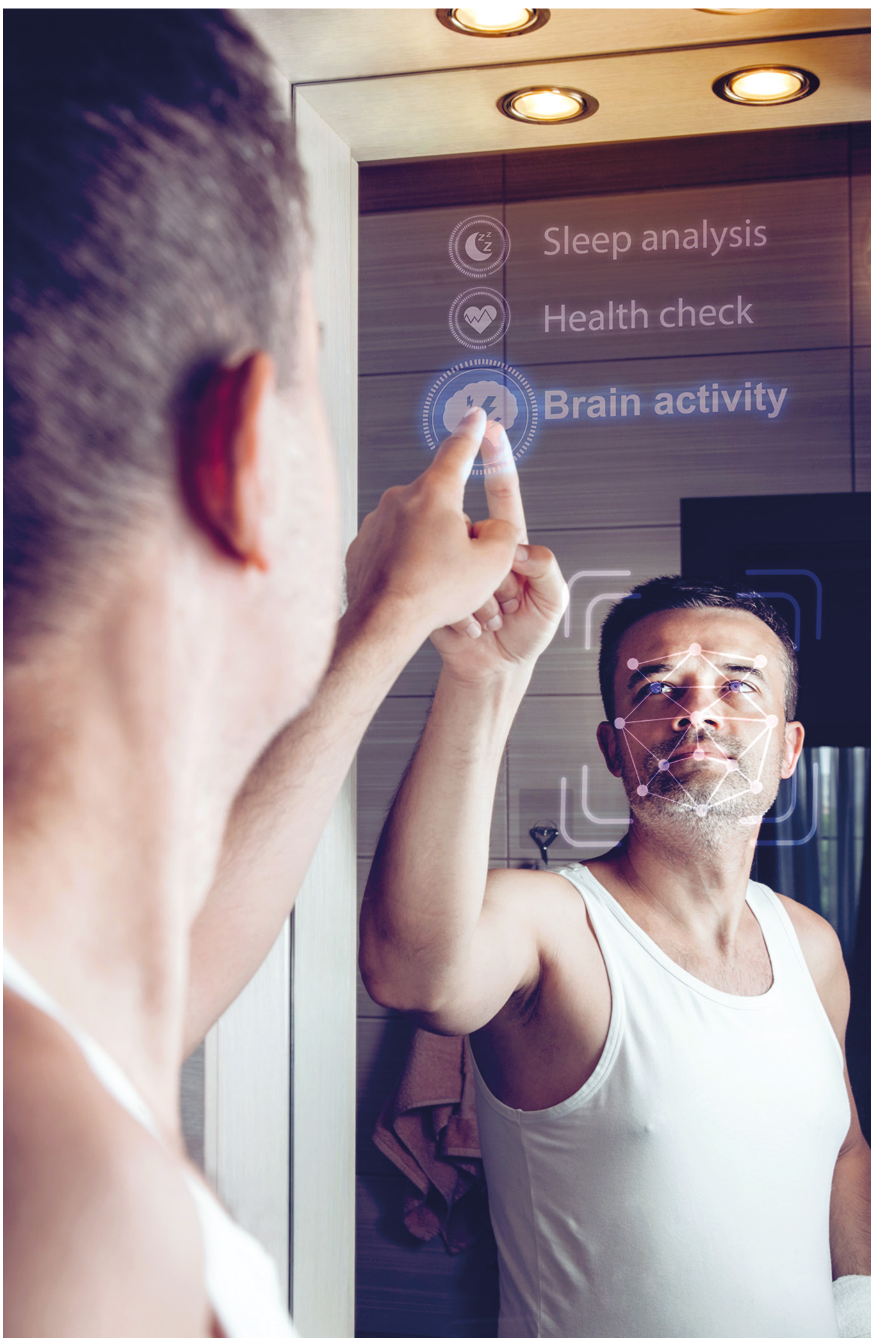
THE TRUE POTENTIAL LIES IN SYSTEMS THAT NOT ONLY CALCULATE, BUT ALSO LEARN FROM THE PATIENT: FROM THEIR SCHEDULES, GLYCEMIC RESPONSE PATTERNS, CULTURAL BACKGROUND, REPEATED HABITS, AND MOST FREQUENT ERRORS



turn nutrition education into a continuous, adaptive, and personalized process that accompanies the patient without imposing an additional cognitive burden. Applied effectively, AI becomes a silent ally that reinforces, supports, and empowers patients in daily life—not replacing the professional, but amplifying their reach.

BEYOND ESTIMATION: TOWARD AI THAT LEARNS FROM THE PATIENT

So far, AI-based nutrition tools have focused on tasks such as food recognition, carbohydrate estimation, and caloric calculation. These are important advances but represent only the surface of what AI can offer.

The real potential lies in systems that not only calculate but also learn from the patient: schedules, glycemic response patterns, cultural context, repeated habits, and frequent errors. This means moving from answering “What does this plate contain?” to addressing more relevant questions, such as “How will this meal affect my glucose level today, in this specific context of stress, prior insulin dosing, subsequent exercise, and room temperature?” That is real personalization. An AI system with such capacity could, for example, anticipate nocturnal hyperglycemia by detecting a dinner richer in fat than usual, or recognize that the patient has had several consecutive days of low physical activity and suggest adjusting their insulin dose or portion size. This is not about replacing clinical judgment but about providing the patient with a tool that acts as a support system—one that thinks with them, not for them.

This type of continuous learning can also identify harmful patterns that may otherwise go unnoticed. If a person consistently underestimates the content of certain foods

» or makes frequent errors at the same time of day, the system could detect this trend and offer practical suggestions without requiring the patient to notice it themselves. That is the key difference between a passive tool and a truly active AI—one that not only responds but anticipates and supports.

CAUTION, LIMITATIONS, AND REMAINING CHALLENGES

Of note, despite their potential, many of these advanced proposals remain largely theoretical, and few of the currently available image-based carbohydrate-counting applications have obtained approval as medical devices from regulatory agencies such as the FDA or CE marking. This means that, while they may be useful as support tools, they should not be used as the sole basis for therapeutic decisions.

Another major challenge is unequal access. Not all patients have the latest smartphones, stable internet connections, or the necessary digital skills to use these tools. Unless this gap is addressed from the outset, there is a risk that AI will become a technology available only to a few, further widening existing health disparities.

Finally, there is the issue of privacy and the use of personal data. These tools process sensitive information: photos of meals, schedules, routines, symptoms, and locations. The question is not only what is done with these data, but also who has access to them, for what purpose, and under what conditions. Patient trust in these systems depends largely on our ability to guarantee that their data are protected and not commercialized.

Despite these barriers, it is clear whether AI is neither a passing trend nor merely a technical advance. It is an opportunity to rethink how we support people with diabetes in one of the most routine yet complex aspects of their treatment: nutrition. The goal is not to delegate to technology what the patient "should already know," but to provide continuous support—to replace pressure with tools that help, ease the burden, and empower.

This transformation does not eliminate the need for nutrition education or the role of health professionals. On the contrary, it amplifies them. We can now go beyond teaching general rules to offering personalized, adaptive, real-time solutions that integrate into patients' lives without overloading them.

The challenge will be 2-fold: first, to ensure that these tools are validated, regulated, and ethically safeguarded; and second, to learn how to incorporate them meaningfully into clinical practice, as part of a patient-centered care strategy. D

CONCLUSIONS

The emergence of AI in nutrition marks a new era in diabetes care. Beyond facilitating carbohydrate counting, these technologies enable a rethinking of educational models—making them contextual, continuous, and truly personalized. Properly integrated, AI does not replace the health professional but amplifies their work and empowers patients, turning each meal into an opportunity for self-care and learning. The challenge now is to ensure that these tools are safe, accessible, and ethically implemented, so that they become part of care centered on people, not just data.

REFERENCIAS

1. Tascini G, Berioli MG, Cerquiglini L, Santi E, Mancini G, Rogari F, et al. Carbohydrate Counting in Children and Adolescents with Type 1 Diabetes. Nutrients. 2018;10(1):109.
2. Housni A, Katz A, Bergeron LJ, Simard A, Finkel A, Roy-Fleming A, et al. Bridging the Gap in Carbohydrate Counting With a Mobile App: Needs Assessment Survey. J Med Internet Res. 2025;27:e63278.
3. Brazeau AS, Mircescu H, Desjardins K, Leroux C, Strychar I, Ekoé JM, et al. Carbohydrate counting accuracy and blood glucose variability in adults with type 1 diabetes. Diabetes Res Clin Pract. 2013;99(1):19–23.
4. Rhyner D, Loher H, Dehais J, Anthimopoulos M, Shevchik S, Botwey RH, et al. Carbohydrate Estimation by a Mobile Phone-Based System Versus Self-Estimations of Individuals With Type 1 Diabetes Mellitus: A Comparative Study. J Med Internet Res. 2016;18(5):e101.
5. Vasiloglou MF, Mougiakakou S, Aubry E, Bokelmann A, Fricker R, Gomes F, et al. A Comparative Study on Carbohydrate Estimation: GoCARB vs. Dietitians. Nutrients. 2018;10(6):741.
6. O'Hara C, Kent G, Flynn AC, Gibney ER, Timon CM. An Evaluation of ChatGPT for Nutrient Content Estimation from Meal Photographs. Nutrients. 2025;17(4):607.
7. Khalifa M, Albadawy M. Artificial intelligence for diabetes: Enhancing prevention, diagnosis, and effective management. Comput Methods Programs Biomed Update. 2024;5:100141.
8. Guan Z, Li H, Liu R, Cai C, Liu Y, Li J, et al. Artificial intelligence in diabetes management: Advancements, opportunities, and challenges. Cell Rep Med. 2023;4(10):101213.
9. López MJ, Vicente M. Apps de diabetes de uso sanitario: regulación y recomendaciones. Rev Diabetes. 2021;14(2):123–30.