# Leveraging AI instant feedback to optimise self-monitoring in weight management

**Authors:**
Dr Victoria Lawson CPsychol (Global Clinical Lead for Psychology), Tobias Larsen (Senior Data Scientist), Lucy Diamond RD (Clinical Director for Innovation), Yves Le Vot (Senior Product Manager - Oviva AG

## Background

Self-monitoring is a behaviour change technique frequently operationalised in weight management interventions through food diaries and other methods of behavioural tracking *(Michie et al, 2013)*. More frequent logs have been linked to greater weight loss *(Samdal et al 2017, Xu et al, 2023)*. However, participants frequently report self-monitoring as unrewarding, citing multiple barriers including boredom, negative affect, avoidance, habit-breaking difficulties, all of which reduce enagement *(Snuggs et al., 2022)*.

## Aims

The BCT behavioural feedback has been shown to increase self-monitoring by strengthening self-efficacy, increasing habit automaticity, and enabling users to adjust behaviours based on insights (Hutchesson et al., 2016; Lally et al., 2010). We tested if adding AI feedback to an established self-monitoring app feature increased habitual meal logging (HML) to logging ≥5 days/week by pairing self-monitoring with behavioural feedback.

## Method

A multidisciplinary team including a health psychologist, dietitian, Product, engineers, and data scientists used the Sprint methodology framework *(Knapp et al., 2016)* to define the overarching BCT pairing concept and subsequent Daily Insights AI components: meal log feedback (a personalised, daily qualitative summary highlighting nutritional successes and areas for improvement), and AI-generated nutrition guidance *(based on WHO guidelines, 2023)*.

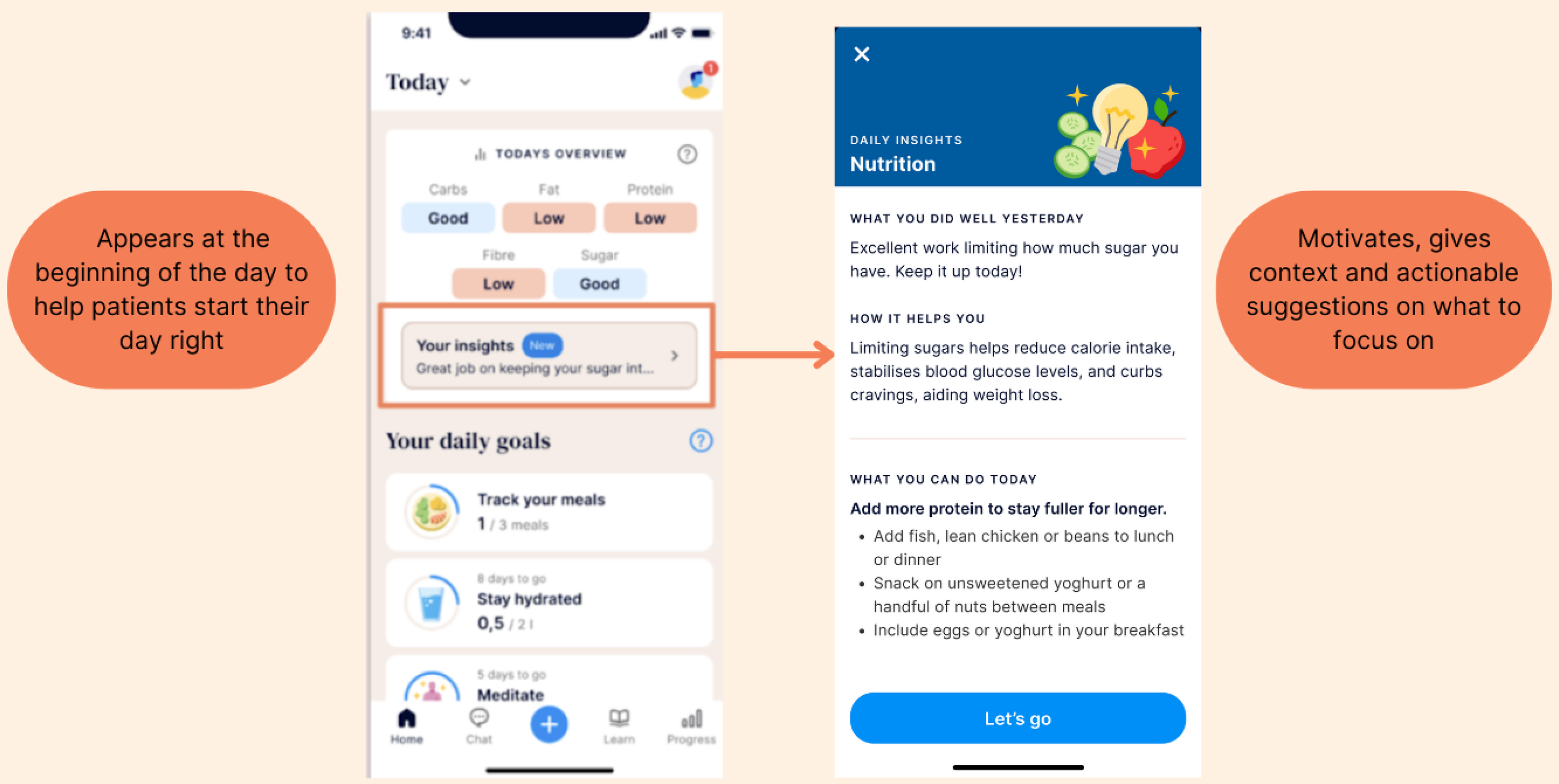


**Figure 1: Daily Insights screenshot**

## Method (continued)

Participants were already enrolled on a 12-week digital weight management intervention provided by a digital weight management service provider. AI optimisation was implemented in July 2024. Results compare % HML in a sample of completers (n=80481) prior to AI introduction to %HML after introduction (n=47589).

## Results

**The integration of AI-driven features led to improvements in HML across all intervention weeks.**

**37.56%**

Average HML logging rate in cohort prior to AI introduction

**43.96%**

Average HML logging rate in cohort with AI introduction

Average HML logging rates in the November cohort (with AI feedback) were 43.96% compared to 37.56% in the June cohort (without AI feedback). Relative uplift ranged from 8.70% (Week 1) to 43.48% (Week 12), with the highest relative gains observed in later journey weeks. Overall, this represented an average uplift of 19.61% in HML following the implementation of new AI app functionalities.

Overall, this represents an average uplift of 19.61% in HML following the implementation of new AI app functionalities.

## Conclusion

The integration of real-time, AI-driven behavioural feedback increased habitual logging, offering a scalable, user-centered intervention to support increased self-monitoring. Future research should include A/B testing to directly evaluate impact on engagement and outcomes. Broader applications of AI in behaviour change will continue to be explored, leveraging the Behaviour Change Taxonomy Ontology *(Marquez et al, 2023)* to enhance intervention design.

All authors employed by Oviva AG.

## References

Hutchesson, M. J., Rollo, M. E., Krukowski, R., Steinbeck, K. S., Collins, C. E., & Harvey, J. (2016). Enhancement of self-monitoring in a web-based weight loss program by extra individualized feedback and reminders: Randomized trial. Journal of Medical Internet Research, 18(4), e192.

Knapp, J., Zeratsky, J., and Kowitz, B. (2016). Sprint: How to solve big problems and test new ideas in just five days. Simon & Schuster.Marques, M. M., Wright, A. J., Corker, E., Johnston, M., West, R., Hastings, J., & Michie, S. (2023). The behaviour change technique ontology: transforming the behaviour change technique taxonomy v1. Wellcome open research, 8.

Lally, P., Van Jaarsveld, C. H. M., Potts, H. W. W., & Wardle, J. (2010). How are habits formed: Modelling habit formation in the real world. European Journal of Social Psychology, 40(6), 998–1009.

Michie, S., Richardson, M., Johnston, M., Abraham, C., Francis, J., Hardeman, W., & Wood, C. E. (2013). The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions. Annals of behavioral medicine, 46(1), 81-95.

Samdal, G. B., Eide, G. E., Barth, T., Williams, G., & Meland, E. (2017). Effective behaviour change techniques for physical activity and healthy eating in overweight and obese adults; systematic review and meta-regression analyses. International Journal of Behavioral Nutrition and Physical Activity, 14, 1-14.

Snuggs, S., Clot, S., Lamport, D., Sah, A., Forrest, J., Helme Guizon, A., & Vogt, J. (2023). A mixed-methods approach to understanding barriers and facilitators to healthy eating and exercise from five European countries: highlighting the roles of enjoyment, emotion and social engagement. Psychology & Health, 1-28.

Xu, R., Bannor, R., Cardel, M. I., Foster, G. D., & Pagoto, S. (2023). How much food tracking during a digital weight-management program is enough to produce clinically significant weight loss?. Obesity, 31(7), 1779-1786.

World Health Organization. (2023). Guidelines on fats, carbohydrates, protein, and dietary fiber intake. Retrieved December 18, 2024, from https://www.who.int