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Artificial Intelligence-Driven Personalized Eating Time Intervention: Precise Practice in the Year of Weight Management

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Abstract. In recent years, using artificial intelligence to recommend individualized eating time has become an emerging direction in weight management. This paper systematically reviews four technical pathways in this field: blood glucose prediction based on continuous glucose monitoring, eating window optimization based on chronotype, metabolic peak prediction based on cortisol load, and dynamic adjustment through multimodal fusion and reinforcement learning. The existing evidence shows a clear gradient. Blood glucose prediction and chronotype-based optimization have accumulated a certain amount of research, but the former is mostly single-modality retrospective analysis and the latter is dominated by cross-sectional studies; cortisol assessment and multimodal fusion are still at an early exploratory stage. At present no study has integrated the above factors into a unified model, and long-term clinical verification is also lacking. This means that "AI-personalized eating time" still has a long way to go from technical feasibility to clinical implementation.

Keywords: artificial intelligence, chrononutrition, personalized eating time, weight management

1. Introduction

In recent years, the number of residents with abnormal body weight in China keeps rising. This is no longer only a small problem at the level of individual health, but has developed into a major public health issue concerning the health of the whole population. In order to implement the decisions of the Party Central Committee, the National Health Commission and 15 other departments jointly launched the Implementation Plan for the "Year of Weight Management" Activity in 2024. The plan proposes relying on artificial intelligence, big data and other technologies to promote personalized weight management, so as to move the prevention and control of chronic diseases forward [1].

However, traditional weight management usually focuses more on increasing physical activity and restricting dietary intake, trying to achieve weight loss by creating an energy deficit [2], but pays little attention to eating time, a key dimension. In fact, circadian rhythm and metabolic regulation are closely related, and unreasonable eating time raises the risks of weight rebound and metabolic disorder [3-6]. Time-restricted eating (TRE) improves metabolism by setting a fixed

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eating window [5, 6], but current studies mostly adopt a uniform protocol, without fully taking the differences in circadian rhythm between individuals into account, so the long-term effect is not ideal [7, 8].

Against this background, chrononutrition has gradually attracted attention. This field systematically examines the interaction between food intake patterns and the endogenous circadian rhythm system, analyzes its influence on weight regulation and metabolic health, and thus provides new ideas for weight management and metabolic improvement [3]. However, determining the optimal eating time for an individual requires the integration of multi-time-point and multi-modal data and the modeling of complex interactions, which traditional methods can hardly handle [9]. At the same time, the popularization of wearable devices and continuous glucose monitoring (CGM) technology has made individualized and continuous collection of physiological data possible [10-12]; machine learning is able to process high-dimensional and non-linear time series data [13] and to dig out the complex association between eating time and metabolic response [14, 15]. On the basis of technical pathways such as CGM-based blood glucose prediction, chronotype recognition and multimodal data fusion, artificial intelligence is expected to realize individualized recommendation of eating time.

However, several key questions in the related research still await answers: How far has clinical verification progressed for the different technical pathways? Are multimodal fusion and dynamic adjustment feasible in actual application? What gaps exist in the current evidence? Around these questions, this review sorts out the technical pathways and the state of the evidence for artificial intelligence-driven personalized eating time intervention, evaluates their maturity and the obstacles to translation, and provides some reference for precise weight management practice under the background of the "Year of Weight Management".

2. Technical pathways

Individualized eating time recommendation needs to answer four questions: (1) At what time of day is eating suitable for this person's blood glucose fluctuation rhythm? (2) At what hour is eating suitable for this person's circadian rhythm? (3) Does the endocrine state at this moment (such as cortisol) tolerate eating? (4) How can it be adjusted dynamically according to daily real-time feedback? The four pathways correspond to the links above respectively, and are reviewed one by one below.

2.1. Blood glucose prediction models based on CGM

CGM devices use subcutaneous sensors to measure interstitial fluid glucose concentration continuously, which can generate a complete 24-hour blood glucose fluctuation curve and derive indicators such as time in range (TIR) and glycemic variability, providing a data basis for individualized blood glucose prediction [11, 16].

2.1.1. Machine learning: random forest/XGBoost for predicting the time of blood glucose peaks

Random forest and XGBoost are two common decision tree ensemble methods, the former reduces variance through parallel ensembling, and the latter optimizes bias through sequential boosting, and both perform well in blood glucose prediction. Quite a few studies have now verified the accuracy of random forest and XGBoost [13] in blood glucose prediction with medium and large samples, and

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their performance is better than that of traditional methods [15, 17, 18]. However, most current random forest/XGBoost blood glucose prediction studies still rely on single-modality CGM data, there is little modeling of the association with eating time and circadian rhythm, and model verification is mostly concentrated on specific populations (such as diabetic patients), so the generalization performance in overweight/obese populations and in populations with different chronotypes remains to be verified.

2.1.2. Deep learning: LSTM modeling of blood glucose fluctuation rhythms

Long short-term memory (LSTM) networks can capture long-term relationships in time series and are suitable for modeling CGM time series data. Existing studies consistently show that LSTM can effectively capture individualized blood glucose fluctuation patterns and make short-term predictions of glucose values, with performance better than that of traditional time series models [19]. At present there are relatively few direct studies of LSTM for modeling blood glucose fluctuation rhythms, the sample sizes are small, most of them focus on short-term prediction (less than 2 hours), and there is a lack of systematic modeling of 24-hour blood glucose fluctuation rhythms; studies of long-period (more than 7 days) rhythm modeling under free-living conditions are few. Meanwhile, the transition from blood glucose prediction to eating time prediction has begun to be explored, but no study has yet used the blood glucose rhythms modeled by LSTM to generate eating time recommendations directly.

2.2. Eating window optimization based on chronotype

2.2.1. The association between chronotype classification and optimal eating time

Sleep chronotype is assessed with the MEQ questionnaire, reflects the intrinsic differences in the circadian phase of individuals, and is divided into morning type, evening type and intermediate type. The metabolic peak of the morning type falls in the early morning, and the metabolic peak of the evening type is relatively delayed [20].

Quite a few large-sample studies show that chronotype is closely related to metabolism. For example, the internal rhythm of evening type individuals is out of phase with social time, and the risks of obesity and diabetes rise markedly [20]. On this basis, chronotype is the key to determining the optimal eating window. The morning type suits an earlier eating window and the evening type a relatively delayed eating window [21]. However, the great majority of current chronotype studies are cross-sectional in design, and prospective interventional studies that turn chronotype classification directly into eating window recommendations are lacking [21]. Research on TRE with a fixed time window still dominates, and algorithmic studies converting chronotype classification into quantifiable eating window parameters are very limited [22].

2.2.2. Eating time optimization driven jointly by the sleep-wake cycle and movement state

The technology for estimating circadian phase with wearable devices is relatively mature [23, 24]. The circadian phase can be identified through the sleep midpoint, activity rhythm and other parameters, and an eating window can then be recommended. Studies have found that the sleep midpoint is related to the timing of the first meal [25]; Phillips et al. used wearable data to quantify postprandial response and circadian rhythm [26]. But most current eating intervention studies assess

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chronotype with the MEQ (Morningness-Eveningness Questionnaire), studies based on wearable estimation of circadian phase are limited, and the sample sizes are small [25, 27].

Movement and sleep state also affect eating time recommendation. Wearable devices can provide parameters such as activity intensity and sleep efficiency, but currently there are few studies that take movement and sleep as independent inputs into the eating window recommendation model, and this still needs verification.

2.3. Metabolic peak prediction based on cortisol load assessment

Cortisol secretion has a circadian rhythm, and an eating time that is out of phase with this rhythm can aggravate insulin resistance and glucose metabolic disorder. For example, eating during the cortisol trough (such as at night) can increase the metabolic burden [28]. Therefore, incorporating cortisol state into the eating time model helps to identify the time windows with poorer metabolic tolerance, and provides an endocrine dimension for the individualized adjustment of the eating window. Wearable devices can indirectly assess cortisol load by collecting data such as heart rate variability, sleep midpoint and deep sleep duration and combining it with machine learning, and then predict the time of the metabolic peak. At present only a few exploratory studies have used data such as heart rate variability (HRV) to assess cortisol grade directly [29], and most studies focus on using HRV to assess stress load. Sleep state is significantly associated with cortisol level [30], but studies applying wearable sleep data directly to assess cortisol load are still very limited; using cortisol concentration as the basis for eating window recommendation has not been confirmed by prospective interventional studies, and the accuracy of estimating cortisol with wearable devices still needs to be verified for consistency with the gold standard (such as salivary or blood cortisol) in large samples. Given the above limitations of single-modality indicators, integrating the cortisol signal with other physiological data for assessment has become a more promising direction.

2.4. Multimodal fusion and reinforcement learning

2.4.1. Hybrid models of CGM, accelerometer and sleep monitoring

The application of multimodal fusion in the research of blood glucose prediction and related metabolism is growing, but it is still mainly exploratory research. Studies have already put forward the concept of digital chrononutrition, that is, realizing precise eating time based on individual circadian rhythm and metabolic pattern by integrating wearable sensors, CGM and smart mobile applications [31]. Some studies have begun to try to fuse CGM with multi-sensor modality data, including heart rate, activity level, sleep pattern and dietary intake. For example, the Bayesian modeling of Phillips et al. included four kinds of data, dietary records, CGM, physical activity, heart rate and heart rate variability, explained up to 15% of the additional blood glucose variance, and improved the accuracy of dynamic blood glucose prediction [26]. Existing fusion studies integrate at most 3-4 modalities and have not yet included cortisol load and chronotype in a unified model at the same time; most multimodal fusion studies focus on blood glucose prediction itself and rarely use the fusion result directly for eating time recommendation; and large-sample, long-term multimodal datasets under free-living conditions are also lacking. Integrating the blood glucose peak estimated by machine learning from CGM, movement and sleep monitoring by wearable devices, cortisol load and circadian rhythm into a multimodal model for eating time recommendation is the gap that this field urgently needs to fill.

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2.4.2. A reinforcement learning framework for dynamically adjusting eating time

On the basis of the initial recommendation provided by multimodal fusion, reinforcement learning (RL) can further adjust dynamically according to individual feedback, and it has particular advantages in dynamic scenarios. Studies have already applied it to dietary recommendation, chronic disease management and other areas [32, 33], and have preliminarily verified its technical feasibility, but current research mainly focuses on "what to eat" or "how much to eat" rather than "when to eat"; most studies remain at the simulation or short-term verification stage, data on long-term effect and adherence in the real world are limited, and its state space has not yet fully integrated multimodal data such as CGM, wearable devices and cortisol status. Therefore, applying RL systematically to the dynamic and personalized recommendation of eating time is still a research direction that urgently needs to be opened up.

2.5. Summary

Table 1. Comparison of current evidence and key limitations across four technical pathways

Pathway	Research basis	Sample size	Key limitations
CGM blood glucose prediction	Numerous retrospective studies and small-sample prospective studies	Large scale (close to ten thousand people)	Single modality, not linked to eating time
Chronotype-based optimization	Relatively many cross-sectional studies	Medium scale (thousands of people)	Mostly cross-sectional, lacking intervention
Cortisol load assessment	Very few proof-of-concept studies	Small to medium scale (13 to more than 600 people)	Indirect estimation, no gold standard verification
Multimodal fusion and reinforcement learning	Very little algorithm development	Very small samples (fewer than 50 people)	Not yet entered clinical verification

Overall, the direction of CGM blood glucose prediction has the largest number of studies and the largest sample sizes, but most of this work stops at the level of predicting glucose values, and research that uses the prediction result further for eating time decisions is still at an initial stage. On the one hand, chronotype-based optimization has accumulated a large amount of cross-sectional evidence, but the conversion into prospective interventional research is still insufficient. On the other hand, the two pathways of cortisol load assessment and multimodal fusion are also at an early exploratory stage, the former lacking gold standard verification and the latter mostly being proof-of-concept and not yet entering the clinical research stage. In terms of the existing evidence, no study has been able to integrate the above five kinds of factors into a unified dynamic recommendation model, and this is exactly the direction that the field most urgently needs to break through.

3. Clinical translation and challenges

3.1. The current state of verification evidence

Judged by the degree of clinical verification, there are rather clear differences among the four technical pathways above.

The first is CGM blood glucose prediction, whose verification basis is relatively more solid. It has both accumulated a good number of retrospective studies and carried out some small-sample prospective studies, and all these works support to different degrees the accuracy of machine

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learning models for blood glucose prediction. However, the complete chain from prediction to clinical decision is still missing verification.

The second is chronotype-based optimization, for which a large amount of cross-sectional evidence has already been accumulated at the population level, but studies that directly use chronotype classification for eating time recommendation and further verify weight or metabolic outcomes are still limited.

The third is that, by comparison, the clinical verification work of the two pathways of cortisol load assessment and multimodal fusion is basically still in a blank state. The former has only a few studies trying to estimate cortisol indirectly with HRV, and the latter is still at the stage of algorithm development and offline dataset verification, and has not been verified in real clinical settings. Overall, this field has accumulated a certain amount in single-modality prediction and basic data collection, but at the level of multimodal integration and clinical translation the evidence still appears insufficient.

3.2. Core obstacles

From technology to the clinic, this translation process will mainly meet the following difficulties.

The first is the difficulty of multimodal data integration. Eating time recommendation needs to integrate multiple data sources such as CGM, wearable devices and cortisol status at the same time, but at present the data formats, sampling frequencies and times of the various devices are not consistent, and there is no unified standard, so it is hard to construct a complete model for clinical application.

The second is that indirect estimation of cortisol lacks gold standard verification. As stated in section 2.3 above, the correlation between HRV and cortisol has been supported in the literature, but the consistency between indirect estimation based on wearable devices and salivary or blood cortisol testing has not been verified in large samples, and therefore it is difficult to serve as an independent basis for clinical decision.

The third is insufficient interpretability of the algorithms. Ensemble learning, deep learning and reinforcement learning and other methods are essentially still black box models, the reasoning process is not transparent enough, and clinicians in scenarios that face patients directly, such as weight management clinics, often find it hard to trust and adopt such recommendation results.

The fourth is the contradiction between clinical endpoint design and the verification period. Changes in body weight and glycemic control usually need a long time to show results, but most studies have only done short-term verification of a few weeks, and the relation between short-term behavior change and long-term metabolic improvement has not yet been well demonstrated, while the complete verification of the effectiveness of one eating time recommendation scheme requires a long research period, difficult follow-up and high cost.

The fifth is that adherence in the real world is still unknown. Existing studies are mostly carried out under strictly controlled conditions, and what behavioral inertia, social pressure and life variability in free-living scenarios bring to the long-term adherence of eating time recommendations has not yet been systematically evaluated.

In addition, in the Chinese context there are also practical constraints such as dietary culture, CGM accessibility and the localization of chronotype assessment tools; the discussion in section 4.1 is relevant here.

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4. Future prospects and conclusion

4.1. Directions for future research

In view of the obstacles above, follow-up research might as well push forward in six directions.

The first is to really build multicenter and standardized multimodal datasets, and to unify the data collection specifications for CGM, wearable devices and cortisol assessment, so that model training and clinical verification will have a shareable data basis.

The second is to make the verification of the accuracy of cortisol estimation solid. After the sample size grows, systematically compare the consistency and the size of the deviation between the cortisol estimated by wearable devices and the gold standard, and further define the range of error at the individual level.

The third is to keep looking for ways to solve the interpretability of the model. Prediction accuracy cannot be sacrificed, and at the same time algorithms with better interpretability can be chosen, or a posterior explanation module can be added, so that the recommendation result has clear physiological logic behind it.

The fourth is to push forward the closed-loop intervention verification from prediction to recommendation. First carry out a small-sample feasibility pilot trial to see how user acceptance and adherence are, and then gradually transition to intervention studies of larger scale, so as to establish a verification path from technical performance to clinical efficacy.

The fifth is to use wearable devices to carry out verification in free-living scenarios, giving play to the advantage of wearable devices and mobile applications in remote data collection, and to test the feasibility and long-term effect of the scheme in real life.

The sixth is to carry out eating time intervention studies for Chinese populations, combining the dietary culture characteristics of Chinese residents and the practical constraints of CGM accessibility, and to explore eating time recommendation strategies suited to the Chinese context.

4.2. Conclusion

This review takes the four technical pathways of artificial intelligence-driven personalized eating time intervention as its main thread and sorts out their current state of clinical verification. From the existing evidence, the basic evidence of the two pathways of CGM blood glucose prediction and chronotype-based optimization is relatively more sufficient, while cortisol load assessment and multimodal fusion are still at an early exploratory stage. Seen from the angle of translation, the current obstacles are mostly concentrated in several aspects, such as multi-source data integration, verification of indirect indicators, algorithm interpretability and clinical endpoint design.

It also needs to be explained that this review includes only the four technical pathways in the scope of analysis, and other dimensions such as behavioral economics and social psychology are not covered; and that part of the included literature belongs to retrospective studies or short-term verification, so the generality of the conclusions still needs to be interpreted carefully by readers.

Under the policy orientation of the "Year of Weight Management", artificial intelligence-driven personalized eating time intervention will have relatively clear application prospects, but there is still a considerable distance between technical feasibility and clinical generalizability. Follow-up research should on the one hand move from single-point prediction to multi-factor integration, and on the other hand let algorithm development gradually transition to clinical verification and extend short-term observation to long-term follow-up, so as to build a personalized weight management scheme that can really be put into practice and really be promoted.

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