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Intelligent Nutrition Technologies in Prenatal Support: Digital Nutrition Personalization for Metabolic and Fetal Health in Pregnant Women

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Abstract

Against the background of a sustained increase in the incidence of gestational diabetes mellitus (GDM) and excessive gestational weight gain (EGWG), the effectiveness of standard population-based dietary recommendations appears to be limited. According to estimates by the International Diabetes Federation (IDF), the global prevalence of hyperglycemia in the prenatal period has reached a critical level, affecting 15,6% of all live births in 2024. A substantial methodological and technological gap is evident, driven by the fragmentation of existing digital solutions: despite compelling results from point solutions, such as the use of artificial intelligence methods for predicting GDM risk and Internet of Things (IoT) systems for continuous monitoring of the condition of pregnant women, these tools are generally not integrated into a single system for supporting clinical and nutrition-related decision-making. In this context, a scientific and practical objective emerges: to develop a holistic concept of digital infrastructure aimed at personalized pregnancy management under increased metabolic risks. Within this objective, the conceptual architecture of an Intelligent Nutrition Platform (INP) is substantiated, intended for comprehensive, dynamic digital personalization of diet and physical activity in pregnant women. A three-level organization of the INP is envisaged, based on multimodal phenotyping, including: real-time recording of physiological parameters using IoT devices, detailed analysis of dietary intake employing computer vision technologies and semantic data processing, and integration of omics information, in particular microbiome profiles. The intelligent core of the platform is built on adaptive ensemble machine learning algorithms operating in an environment protected by a blockchain architecture, which ensures interoperability, integrity, and confidentiality of data at all stages of their lifecycle. It is expected that the implementation of the INP will substantially increase the accuracy of early prediction of metabolic risks during gestation, strengthen pregnant women's adherence to personalized nutritional and behavioral interventions and, consequently, improve key indicators of maternal metabolic status as well as fetal growth and development.

Keywords: *Intelligent Nutrition Science, Prenatal Support, Digital Personalization, Gestational Diabetes, Artificial Intelligence, Fetal Health, IoT, Blockchain, Multimodal Phenotyping.*

INTRODUCTION

Optimal nutrition during pregnancy is a key determinant of maternal and fetal health, shaping metabolic trajectories not only throughout gestation but also over the subsequent life course. Metabolic disturbances arising during the gestational period are associated both with immediate risks, such as an increased likelihood of obstetric and neonatal complications, and with long-term consequences, including an elevated risk of developing chronic non-communicable diseases in the mother and child [1]. Despite the availability of detailed clinical guidelines regulating target ranges of gestational weight gain, the structure of a balanced diet, and the need for timely micronutrient support [8], global epidemiological trends indicate a deterioration of key indicators of metabolic health during pregnancy.

The global incidence of gestational diabetes mellitus (GDM) has reached levels that may be qualified as critical: according to estimates by the International Diabetes Federation (IDF) for 2024, hyperglycemia during pregnancy is associated with 15,6% of all live births [1]. High-income countries demonstrate a sustained upward trend. In particular, in the United States between 2016 and 2022, the frequency of GDM increased from 60 to 81 cases per 1000 live births [10], which reflects a systemic mismatch between the preventive potential of existing population-based clinical protocols and their real-world performance. The observed increase indicates that standardized preventive measures do not provide sufficient sensitivity to individual risk factors and patterns of behavioral response.

In parallel, the importance of the problem of excessive gestational weight gain (EGWG) is increasing. The prevalence of EGWG reaches 53% among pregnant women with pre-existing overweight or obesity [2], which makes this phenomenon one of the most powerful clinical predictors of adverse pregnancy outcomes. Clinical data from 2023 demonstrate a statistically significant association between

EGWG and an increased risk of gestational hypertension (risk ratio 5,85) and a higher frequency of operative delivery [3]. The high prevalence of GDM and EGWG creates a pronounced socio-economic burden, since GDM is an important risk factor for the development of type 2 diabetes mellitus in the mother within the subsequent 5–10 years and is also associated with an increased likelihood of obesity and type 2 diabetes in the offspring [1]. Effective interventions implemented in the prenatal period therefore acquire strategic importance for the long-term reduction of chronic non-communicable disease incidence at the population level.

Traditional dietary approaches based on generalized recommendations for broad population groups demonstrate limited effectiveness in managing metabolic risks during pregnancy. One of the key reasons is the pronounced interindividual variability of metabolic responses to identical nutrient loads [11], which makes it impossible to achieve optimal results using uniform protocols. This circumstance necessitates a transition to precision nutrition science, focused on dynamic, data-driven strategies whose implementation is fundamentally feasible only under conditions of integration of intelligent digital technologies.

In the context of digital health, recent years have seen substantial progress in the development of components potentially applicable in obstetric practice. Artificial intelligence (AI) has demonstrated high effectiveness in the analysis of medical images for fetal biometry [12] and, of particular importance for nutrition science, in the early prediction of risks of metabolic complications. Systematic reviews indicate that about 85% of studies devoted to the use of AI in the context of GDM are focused on constructing predictive models based predominantly on retrospective data for risk stratification [4]. In the field of continuous monitoring, the Internet of Things (IoT) enables high-precision real-time phenotyping: wearable devices have been validated for clinically meaningful tracking of physiological parameters, including heart rate variability [5]. To ensure trust in medical data management systems, the implementation of blockchain technologies is being considered, allowing secure storage, traceability, and interoperability of personal medical information [5].

At the same time, an analysis of the current scientific literature reveals a critical gap associated with technological fragmentation, or siloing, of digital solutions. Individual technological components – AI systems focused on prediction, IoT platforms for continuous monitoring, and blockchain systems for ensuring data security – function autonomously without forming a unified integration framework. There is no holistic platform capable of integrating continuous data collection, dynamic risk prediction, and automated, clinically relevant feedback to support real-time decision-making [5, 6]. Existing solutions are predominantly limited to prediction functions and are not connected to continuous monitoring systems, which prevents the implementation of a closed loop monitoring – analysis – intervention – feedback necessary for genuinely dynamic personalization of prenatal support.

Against this background, the **objective** is the conceptual design and substantiation of the architecture of a platform capable of integrating real-time data obtained through IoT-based phenotyping, omics indicators, including microbiome characteristics, and adaptive ensemble machine learning algorithms within a single management framework protected by blockchain technologies.

The **scientific novelty** of the approach lies in the fact that, for the first time, an architecture is proposed that is oriented not only toward risk prediction but also toward their prompt correction through dynamic modification of the prenatal diet and physical activity regimen based on a continuously updated array of multimodal data.

Within this concept, the **authors' hypothesis** is put forward that the use of an Intelligent Nutrition Platform (INP), based on the principles of digital personalization, contributes, first, to increasing pregnant women's adherence to individualized recommendations and, second, to a statistically significant reduction in the risk of developing metabolic complications, primarily GDM and EGWG, as well as the frequency of adverse fetal outcomes. The implementation of such a platform-based model has the potential to transform the paradigm of prenatal care, shifting the focus from reactive management of complications to proactive, continuously adaptable management of metabolic risks.

MATERIALS AND METHODS

The study is based on the methodological framework of a systematic review and literature synthesis followed by conceptual modelling of the system architecture. The theoretical and methodological foundation consisted of a body of publications devoted to digital health, the use of artificial intelligence and machine learning methods (AI/ML), as well as precision nutrition science in obstetric practice.

The key analytical method was comparative analysis, applied, on the one hand, to assess the effectiveness and robustness of machine learning algorithms in solving predictive tasks, primarily in the context of gestational diabetes, and, on the other hand, to identify the most effective approaches to the collection and integration of multimodal data. This approach made it possible to compare different model architectures, types of features used, and training strategies in terms of their predictive value and clinical applicability.

The central research tool was conceptual modelling aimed at developing the system architecture of an integrated Intelligent Nutrition Platform (INP). The design logic of the modelling was based on the need to overcome technological fragmentation and to ensure coherent interaction of heterogeneous components – AI modules, IoT infrastructure, and blockchain solutions – within a single framework.

Particular emphasis was placed on the ability of the system to operate in real time, supporting adaptive, dynamically adjustable interventions as opposed to static, one-off recommendations.

The source base was formed with a priority on relevance and scientific authority, predominantly for the period 2019–2024. Approximately 90% of the included materials are peer-reviewed scientific publications from leading international databases such as Scopus, Web of Science, IEEE, and ACM, which ensured a high level of methodological rigor and reproducibility of results. The remaining approximately 10% consisted of analytical reports by major consulting firms and international organizations, including in particular data from the International Diabetes Federation (IDF), which have significant normative and epidemiological value.

The body of sources was structured into three substantively interconnected groups. The first group included epidemiological and clinical data reflecting the prevalence of key metabolic risks such as gestational diabetes and excessive gestational weight gain, as well as authoritative guidelines and recommendations on prenatal nutrition and nutrient support. The second group covered studies on the use of AI/ML in nutrition, including the application of deep learning and computer vision methods for dietary analysis, as well as the development and validation of machine learning predictive models aimed at assessing individual risks of metabolic complications. The third group was devoted to infrastructural solutions and focused on the use of Internet of Things technologies for continuous monitoring of physiological parameters, as well as on blockchain architectures designed to ensure the security of medical data, their traceability, and the interoperability of heterogeneous information systems. This classification of the source base provided a holistic view of both the clinical and epidemiological context and the technological prerequisites for the development of an integrated intelligent platform.

RESULTS AND DISCUSSION

The increase in the prevalence of GDM and EGWG in recent years cannot be explained solely by demographic shifts such as aging of the maternal population or changes in the structure of obesity in the general population; it indicates a systemic limitation in the effectiveness of existing approaches to lifestyle and nutritional management during pregnancy. The dynamics of GDM indicators in the United States, where the frequency of this complication increased from 60 to 81 cases per 1000 live births [10], demonstrate that standard interventions based on unified clinical protocols and population-based recommendations endorsed by authoritative professional associations do not provide a sufficient level of prevention of metabolic disorders. This situation provides a compelling basis for the conclusion that overcoming adverse epidemiological trends requires not a cosmetic modification of existing recommendations, but a qualitative transition to digitally enhanced, personalized strategies for pregnancy management.

The fact that GDM acts as a powerful predictor of the development of type 2 diabetes in the mother and an increased risk of obesity and T2D in the offspring [1] confers on prenatal intervention using an Intelligent Nutrition Platform (INP) not only a clinical but also a pronounced economic dimension. Early prevention or effective management of GDM and EGWG in the early stages of pregnancy can substantially reduce the cumulative healthcare costs associated with the treatment of chronic non-communicable diseases linked to metabolic dysfunction. In this context, the implementation of an INP can be considered an investment strategy aimed at reducing the long-term financial burden while simultaneously improving health outcomes in the current and subsequent generations.

Table 1 reflects the dynamics of the prevalence of key metabolic risks in the prenatal period for the years 2016–2024.

Table 1. Dynamics of the prevalence of key metabolic risks in the prenatal period (2016–2024) (compiled by the author based on [1, 2, 10])

Metabolic risk indicator	Statistics (period/ geography)	Clinical consequences	Relevance for personalization
Prevalence of gestational diabetes mellitus (GDM)	15.6% of live births (IDF estimate 2024)	Risk of type 2 diabetes in the mother and child, macrosomia, offspring obesity	Requires dynamic glycemic monitoring and real-time dietary adaptation
Growth rate of GDM (USA)	Increase from 60 to 81 per 1000 live births (2016–2022)	Reflects the inefficiency of current population-level prevention strategies	Necessitates early ML-driven screening and precision nutrition (PN)
Prevalence of excessive weight gain (EWG)	53% among women with overweight/obesity (2023)	Preeclampsia, gestational hypertension, caesarean section	Requires integration of nutritional support and personalized physical activity

The transition to precision nutrition science implies the use of algorithms capable of processing highly heterogeneous datasets that extend far beyond traditional clinical and anamnesis-based indicators. Within this paradigm, the key methodological foundation of the architecture of Intelligent Nutrition Platforms (INP) is multimodal phenotyping, which enables coordinated analysis of behavioral, physiological, and molecular-biological parameters [7]. A central role in this is played by continuous real-time data collection using wearable devices and IoT sensor systems that generate a constant stream of physiological information. Modern smartwatches demonstrate near-medical accuracy in recording heart rate and heart rate variability [5], which allows INP algorithms to dynamically assess the level of metabolic stress, actual energy expenditure, and sleep structure characteristics. In combination with data from continuous glucose monitoring (CGM) systems, such a sensor configuration provides not only diagnostics but also a continuously updated assessment of cardiometabolic status with the possibility of immediate adjustment of behavioral and dietary recommendations in response to detected deviations [13].

An important component of precision nutrition science is also the use of artificial intelligence methods for high-precision accounting of dietary intake. The use of computer vision and deep learning makes it possible to radically reduce dependence on subjective and typically inaccurate self-reports of nutrition [6]. Models trained on large datasets are capable of reliably recognizing the composition of dishes, identifying ingredients, estimating portion sizes, and automatically reconstructing the nutrient profile based on both images and textual recipes [6]. In this context, the accuracy of capturing actual nutrient intake serves as a fundamental prerequisite for the development of genuinely precision dietary strategies. The final level of personalization is the integration of omics data, primarily markers reflecting the individual biological response to diet. Analysis of the gut microbiota, as well as other omics characteristics, makes it possible to algorithmically model how the body of a particular woman metabolizes incoming nutrients and to identify targets for tailored nutritional interventions. It has been shown that the implementation of such a precision approach, in particular through the development of microbiota-directed complementary foods (MDCF), can optimize metabolic pathways related to growth, immune function, and bone health [7]. Integration of these data into the INP makes it possible to move from universal, averaged recommendations to the formation of dietary regimens aimed at optimizing individual metabolic processes in a maximally personalized format.

Below, Table 2 presents a classification of input data modalities for the Intelligent Nutrition Platform.

Table 2. Classification of input data modalities for the Intelligent Nutrition Platform (compiled by the author based on [5-7]).

Data modality	Key input parameters	Technology for acquisition/ analysis	Functionality in INTP
Physiological (real time)	Glucose (CGM), HR, physical activity, sleep, body weight	IoT, smart devices, validated sensors (2023)	Dynamic assessment of energy expenditure, glycemic and cardiometabolic status
Nutritional (CV/NLP)	Ingredient/portion recognition, nutrient profile	Deep learning (CNN), semantic analysis, recommender systems	Automated and accurate accounting of actual diet, elimination of self-report errors
Biological (omics)	Metabolomics, gut microbiota composition	Sequencing, precision nutrition approach	Development of individual food matrices, correction of metabolic pathways

The effectiveness of an Intelligent Nutrition Platform (INP) is largely determined by its computational capacity and by the choice of the class of algorithms underlying its analytical core. In current practice, machine learning methods demonstrate high potential for predictive modelling of gestational diabetes mellitus (GDM), with the most widely used algorithms being classical approaches, including logistic regression (LR) and random forest (RF) [4]. At the same time, accumulated data indicate that the use of more complex architectures, in particular artificial neural networks (ANN), is associated with improved prediction quality, which is reflected in higher values of key prognostic metrics such as the area under the ROC curve (AUC) compared with traditional models.

Further, Figure 1 visually presents an analysis of the averaged performance metrics (AUC) of AI models for GDM prediction.

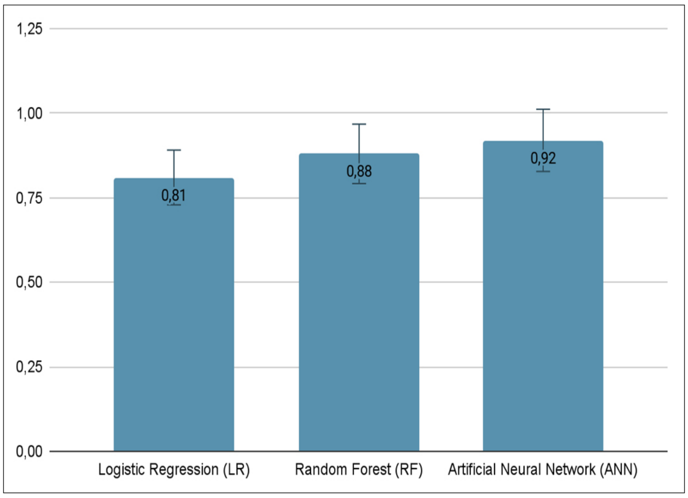

Fig. 1. Comparative analysis of average performance metrics (AUC) of AI models for forecasting GDM (compiled by the author based on [4]).

Despite the high accuracy of predictive models, the fact that approximately 85% of AI studies in the field of GDM are focused on prediction tasks indicates a pronounced methodological deficit in the area of dynamic, interventional management [4]. To realize the potential of an Intelligent Nutrition Platform (INP), it is necessary to move from static models based predominantly on retrospective data to adaptive algorithms, such as reinforcement learning methods, capable of continuously revising and adjusting recommendations depending on the current state of the patient. A predictive model built on a set of risk factors makes it possible only to identify an increased probability of GDM development, whereas an adaptive architecture integrated with data streams from IoT devices enables immediate modification of diet or physical activity level in response to a specific physiological trigger, for example, a change in glycemic response to a particular food product. The ability for such continuous, context-dependent correction constitutes the fundamental distinction of an INP from traditional clinical decision-support systems.

A substantial obstacle to the creation of a truly comprehensive prenatal digital ecosystem remains technological fragmentation, in which IoT infrastructure, artificial intelligence modules, and security systems function as isolated components [5]. The conceptual model of an INP is aimed at overcoming this siloing by forming a closed loop in which data collection, analytical processing, and subsequent intervention constitute a single, continuously functioning cycle. The integration of AI and IoT creates a mechanism of constant feedback: sensors record indicators of the actual state, including heart rate, level of physical activity, and other parameters; the intelligent core compares them with individualized target ranges and generates adapted recommendations. When a critical level of the weight gain index (EGWG) is reached or in the presence of persistently insufficient physical activity, the platform is capable of promptly adjusting the nutrition plan and simultaneously proposing exercises that are safe from the standpoint of prenatal fitness.

The infrastructural layer built on the principles of blockchain technology plays a system-forming role in ensuring security and interoperability [5]. The immutability of records in a distributed ledger makes it possible to guarantee the integrity and protection of sensitive data, from omics profiles to personal health information (PHI). In this way, conditions are created for confidential yet transparent and traceable data exchange between heterogeneous healthcare information systems and the patient's personal platform, which substantially reduces the severity of compatibility barriers typical of clinical practice.

The concept of an INP is aimed at scaling a highly qualified, interdisciplinary approach to prenatal support, in which nutrition and physical activity are regarded as integrated components of a single system for managing metabolic health. The practice of specialists with qualifications as dietitian-nutritionists (EQF5, NASM Nutrition Coach) and prenatal fitness instructors demonstrates that effective prevention and correction of metabolic disorders are impossible if the intervention is reduced solely to dietary restrictions; precise, adaptive coordination of dietary strategies and physical activity is required [8]. The INP functionally reproduces and scales this expert approach, providing, in particular, two key data-driven directions of intervention.

The first direction is related to precision diet therapy aimed at optimizing glycemic control. Whereas a traditional nutrition specialist relies predominantly on population-based recommendations, the INP, using multimodal phenotyping, including omics indicators and the profile of glycemic responses, generates individualized food matrices [7]. When a persistently unfavorable glycemic response to certain carbohydrates is identified, the algorithm does not limit itself to their direct exclusion from the diet but instead constructs a consumption regimen that takes into account combinations with dietary fibers or protein, adapted to the characteristics of the specific microbiome. This level of fine-tuned adjustment makes it possible to substantially enhance glycemic control and thereby increases the likelihood of preventing or more effectively managing GDM [7].

The second direction is associated with dynamic management of physical activity, which is critically important for controlling EGWG. For a pregnant woman, an exercise program must be not only effective but also demonstrably safe [2]. The INP uses IoT data on the current functional state and individual risk profile to continuously adapt the exercise plan. When wearable devices register signs of stress, cardiometabolic overload, or other alarming signals, the algorithm, constructed according to principles comparable to the competence of a prenatal fitness instructor, automatically reduces the recommended intensity or transforms the type of exercise. This mode of continuous monitoring simultaneously minimizes the risk of complications and strengthens adherence, since the proposed interventions are constantly aligned with the patient's current physiological state. In this configuration, the INP effectively acts as a high-precision, continuously functioning digital assistant that enables a single expert to support a significantly larger number of patients without reducing the level of personalization.

Full-scale clinical implementation of such platforms requires consideration of a number of substantial methodological, ethical, and legal constraints. One of the most significant methodological barriers remains the low degree of external validation of ML models. Most high-performance AI algorithms used for GDM prediction have not yet been tested in prospective, multicenter studies on heterogeneous populations, including non-clinical populations [4]. In the absence of such validation, it is impossible to reasonably assert that the results demonstrated in experimental or retrospective samples will be reproducible in a real-world clinical setting.

Additional challenges include problems of transparency and data bias. The effectiveness of AI algorithms in the field of maternal health is directly determined by the quality, volume, and diversity of training datasets. The lack of large, representative, open datasets creates a risk of algorithmic bias, in which an INP may be less accurate or clinically ineffective for certain demographic groups, thereby exacerbating existing disparities in access to high-quality medical care [15]. At the same time, the explainability of decisions becomes critically important: the absence of mature explainable AI (XAI) mechanisms sustains the black box phenomenon, making it impossible for a physician or patient to reconstruct the logic behind a complex recommendation, especially when it concerns aspects critical to fetal health [4].

Finally, the use of multimodal, omics, and physiological data in real time requires the formalization of robust ethical, legal, and regulatory frameworks. Although the use of blockchain technologies partially addresses challenges related to data confidentiality and integrity [5], there remains a need for clear classification of an INP as a medical device. Since the platform generates active, interventional recommendations, including interventions aimed at glycemic control, it should be subject to strict requirements comparable to regulatory standards for traditional medical devices, encompassing safety, clinical effectiveness, risk management, and accountability for decision-making.

CONCLUSION

The conducted study has confirmed the high importance of developing precision nutrition interventions against the background of a sustained increase in metabolic disorders in the prenatal period, including gestational diabetes mellitus (GDM), identified in 15,6 % of live births, and excessive gestational weight gain (EGWG), recorded in 53 % of women from risk groups. The conceptual objective, which consisted in shaping the architecture of an integrated Intelligent Nutrition Platform (INP), was achieved through the systematic synthesis of functional requirements for artificial intelligence components, IoT infrastructure, and blockchain technologies.

The proposed INP concept eliminates the problem of technological siloing by forming a closed loop that begins with multimodal phenotyping — integrating physiological parameters, data on nutrient profile, and microbiome characteristics — and ends with the dynamic generation of personalized recommendations. The use of modern machine learning algorithms ensures not only high predictive accuracy in assessing the risk of metabolic disorders but also, crucially, the possibility of continuous adaptation of nutrition and physical activity plans in accordance with the individual metabolic response of each woman. The infrastructural use of blockchain technologies creates a foundation for secure and interoperable handling of data, which is a key prerequisite for trustworthy and effective clinical application of the platform.

From a practical standpoint, the INP can be regarded as a tool for transforming the healthcare system from a predominantly reactive model focused on treating already established complications toward preventive and precision medicine. For highly qualified specialists in nutrition science and prenatal fitness, the platform serves as a means of scaling their evidence-based expert practice: detailed, comprehensive recommendations that previously required in-person interaction and labor-intensive manual data collection are translated into a format of continuous digital support. This, in turn, contributes to increased patient adherence and improved control of body weight and glycemia.

Further development and clinical implementation of an INP presuppose the solution of a number of critical research tasks. First, it is necessary to conduct large-scale prospective, multicenter randomized controlled trials to provide external validation of integrated ML models in heterogeneous clinical populations. Second, the development of standards for explainable artificial intelligence (XAI) becomes a priority, as this will ensure transparency of algorithmic decisions, strengthen clinical trust, and facilitate integration of the platform into existing clinical decision-support systems. Third, in-depth studies of omics data, primarily the microbiome, are needed to increase the accuracy of nutrition recommendations and to achieve a more comprehensive understanding of their impact on long-term fetal and maternal metabolic outcomes.

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