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IMPACT OF REMOTE MONITORING USING AN AI-POWERED VOICE-ACTIVATED ROBOTIC ASSISTANT ON THE DYNAMICS OF METABOLIC PARAMETERS: RESULTS OF A PROSPECTIVE COMPARATIVE STUDY

<i>Aim</i>	To evaluate the impact of remote patient monitoring (RPM) via an artificial intelligence (AI)-driven voice robotic assistant (VRA) on markers of visceral adiposity (lipid accumulation product [LAP] index and visceral adiposity index [VAI]), glycemic control, and quality of life in patients with type 2 diabetes mellitus (T2DM) and obesity.
<i>Material and methods</i>	This prospective, open-label, comparative study included 121 patients with obesity and T2DM. Participants were divided into an observation group (n=71; standard care + daily AI-assisted monitoring) and a control group (n=50; standard care only). The follow-up period was one month.
<i>Results</i>	After one month, the observation group showed a statistically significant reduction in the LAP index by 25.9% (p<0.001) and VAI by 31.2% (p<0.001). Fasting blood glucose concentrations decreased by 15.1% (p<0.001). No significant changes were observed in the control group at one month. Intergroup differences at one month were statistically significant for both the LAP index (p=0.004) and VAI (p=0.007). Quality of life (SF-36) also improved significantly in the observation group (+7 points vs. +1 point in the control group; p<0.001).
<i>Conclusion</i>	Implementing a RPM program integrated with an AI-driven voice assistant for patients with obesity and T2DM significantly enhances the control of visceral obesity markers, glycemic levels, and quality of life, which effectively mitigates the risk of cardiometabolic disorders.
<i>Keywords</i>	Remote patient monitoring; metabolic syndrome; type 2 diabetes mellitus; obesity; artificial intelligence; robotic voice assistant; visceral adiposity; LAP index; cardiometabolic risk.
<i>For citations</i>	Chumalaeva Sh.R., Kozhevnikova M.V., Zektser V.Yu., Mesitskaya D. F., Khabarova N. V., Belenkov Yu.N. Impact of Remote Monitoring Using an AI-Powered Voice-Activated Robotic Assistant on the Dynamics of Metabolic Parameters: Results of a Prospective Comparative Study. <i>Kardiologiia</i> . 2026;66(3):3–11. [Russian: Чумалаева Ш. Р., Кожевникова М. В., Зекцер В. Ю., Меситская Д. Ф., Хабарова Н. В., Беленков Ю. Н. Влияние дистанционного мониторинга с использованием голосового роботизированного ассистента на основе искусственного интеллекта на динамику метаболических показателей: результаты проспективного сравнительного исследования. <i>Кардиология</i> . 2026;66(3):3–11].
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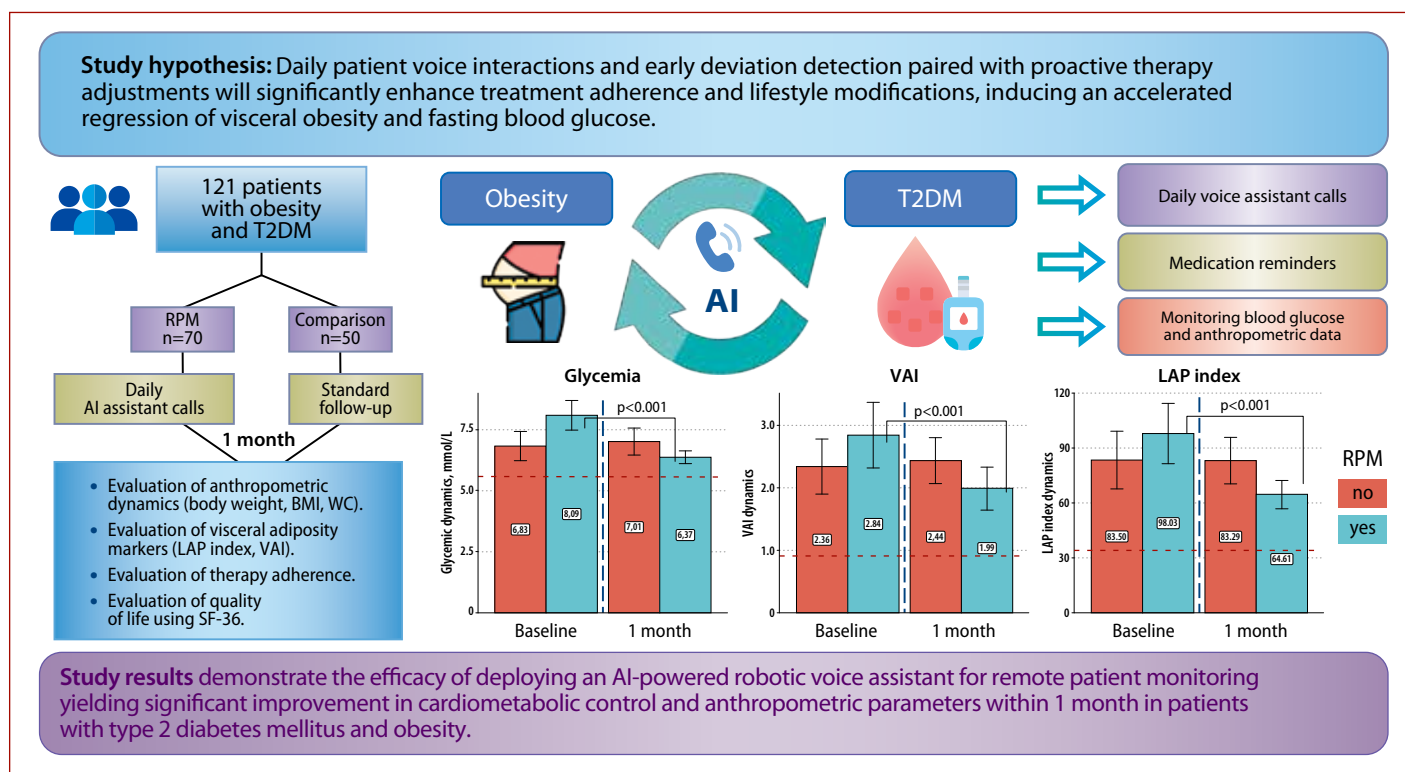
Introduction

The rising prevalence of chronic non-communicable diseases represents a pressing challenge for modern global healthcare. Obesity and type 2 diabetes mellitus (T2DM) have reached pandemic proportions, remaining the leading drivers of cardiovascular morbidity and mortality worldwide [1]. Despite an ever-expanding pharmacotherapeutic arsenal, the long-term management of these patients remains suboptimal. This limited efficacy stems primarily from poor treatment adherence and the constraints of traditional, episodic outpatient models, which lack the requisite frequency and intensity of patient-provider interaction [2, 3]. Consequently, there is an urgent need for interventions targeting the early detection and timely modification

of non-communicable disease risk factors. In several countries, the deployment of modern technologies, including those powered by artificial intelligence (AI), ensures the early-stage detection of risk factors and complications associated with chronic non-communicable diseases, thereby enhancing treatment efficacy and improving the quality of healthcare delivery [4].

To address the suboptimal efficacy, limited accessibility of current follow-up models, and poor treatment adherence, remote patient monitoring (RPM) technologies have increasingly gained attention [5]. Concurrently, recent research underscores the clinical utility of these remote modalities. For example, L. A. Suplotova et al. (2025) [6] demonstrated that remote monitoring of self-monitored blood glucose in patients with

Central Illustration. The impact of AI-powered remote monitoring on metabolic parameter dynamics: Results of a prospective comparative study



BMI, body mass index; WC, waist circumference; LAP, lipid accumulation product, a marker of cardiometabolic risk; VAI, visceral adiposity index; T2DM, type 2 diabetes mellitus; AI, artificial intelligence; RPM, remote patient monitoring; SF-36, 36-item short form health survey for quality-of-life assessment.

Study scheme explanation:

The study enrolled 121 patients with obesity and T2DM. 71 of them were monitored remotely via a robotic voice assistant; 50 patients served as the comparison control group. Group 1: Daily automated calls from the AI assistant; Group 2: Standard-of-care clinical follow-up. Study duration: 1 month.

Evaluated Parameters:

Anthropometric metrics (body weight, BMI, and WC; visceral adiposity markers (LAP and VAI); therapy adherence; treatment compliance; quality of life assessed via the SF-36 questionnaire; fasting blood glucose.

Key visual elements for the diagram

Daily AI voice assistant calls: the primary digital health intervention method; glycemic and anthropometric monitoring: routine patient data collection and tracking; medication reminders: the core element for improving compliance; study aim: evaluation of AI-assisted RPM on cardiometabolic and anthropometric parameters in patients with T2DM and obesity over a 1-month period.

type 1 DM yielded a significant reduction in glycated hemoglobin (HbA1c), increased glucose time-in-range, and enhanced quality of life compared to conventional care. These findings further substantiate the therapeutic potential of remote health technologies in DM management [6].

Economic evaluations indicate that implementing these automated RPM systems yields substantial cost-effectiveness by reducing clinical consultation times, optimizing patient routing, and consequently mitigating the financial burden of managing long-term complications [7].

Paradoxically, however, many current digital health platforms inadvertently erect a new barrier: the “digital divide” [8]. Because these systems demand smartphones, specialized applications, and a high degree of technical proficiency, they often worsen digital health

inequities. This issue is particularly acute among older adults, a demographic cohort that represents a substantial portion of the T2DM population, yet is frequently marginalized during the digital transformation of healthcare [8].

AI-powered voice assistants utilizing natural language interfaces offer a promising solution to this dilemma. By providing an intuitive, user-friendly modality that requires no specialized technical proficiency, these tools hold significant potential to enhance patient engagement and treatment adherence while mitigating age-related and technological barriers [9]. Systematic reviews underscore that healthcare provider-led telemonitoring is consistently associated with optimized glycemic control in patients with DM [10–12].

A growing interest in digital health interventions is similarly evident within clinical practice in Russia. In

a recent systematic review, V. V. Chichkova et al. (2025) highlighted a substantial increase in the deployment of digital technologies for patient education in T2DM. Notably, the integration of telemedicine modalities not only elevates patient satisfaction but also yields improvements in glycemic control comparable to conventional in-person instruction. Nevertheless, contemporary digital solutions remain localized primarily around educational components, whereas the therapeutic capacity of AI-powered voice assistants to facilitate comprehensive remote patient monitoring, particularly regarding medication adherence assessments and regimen optimization, remains largely unexplored [13].

Concurrently, existing studies focus predominantly on evaluating the long-term (6–12 months) impact of these interventions on conventional metrics, such as HbA1c. Conversely, data regarding the short-term effects of remote monitoring on more sensitive, pathogenetically relevant markers of cardiometabolic risk, specifically those reflecting visceral adiposity, remain critically scarce. The Lipid Accumulation Product (LAP) index and the Visceral Adiposity Index (VAI) are now widely recognized as more sensitive, early-stage indicators of visceral adipose tissue accumulation and associated cardiometabolic risk than conventional metrics like body mass index (BMI) [12]. To our knowledge, no randomized controlled trials have yet evaluated the impact of an AI-powered voice assistant-based RPM on the dynamics of LAP and VAI.

Aim

This study aimed to determine the efficacy of an AI-powered robotic voice assistant (RVA)-integrated RPM program in modulating markers of visceral adiposity (the LAP index and VAI), glycemic control (fasting plasma glucose), and quality of life among patients with T2DM and obesity.

Study hypothesis: We hypothesized that daily AI-driven voice interactions, by simulating continuous clinical guidance, would significantly potentiate changes in treatment adherence and lifestyle modifications, which would be objectified by the regression of visceral obesity, evaluated by the dynamics of the LAP index and VAI, already in the short term.

Material and methods

Study design

This single-center, prospective, open-label, comparative, controlled study was conducted at University Clinical Hospital No. 1 of Sechenov University (Moscow) from November 2024 through May 2025. The study protocol was approved by the local ethics committee

(Protocol No. 26–24, October 24, 2024). All participants provided written informed consent. The study design adheres to the CONSORT standards [14].

Inclusion and exclusion criteria

Patients aged 18–85 years with confirmed obesity and T2DM were included in the study. Diagnoses were established according to the International Diabetes Federation (IDF, 2005) criteria, which required the presence of abdominal obesity, defined as a waist circumference (WC) ≥ 94 cm for men and ≥ 80 cm for women [15].

Exclusion criteria:

- history of acute cardiovascular complications (CVCs) (myocardial infarction, stroke) within the past 6 months;
- stage 4–5 chronic kidney disease (glomerular filtration rate [GFR] < 30 mL/min/1.73 m²);
- severe hepatic impairment (Child-Pugh class C);
- active malignancy;
- diagnosed psychiatric disorders that preclude meaningful interaction with the study device;
- lack of reliable access to a cellular network.

The exclusion criterion for patients without reliable access to cellular communication was dictated by the technical specifications of the RPM system used: the voice-based AI assistant operates via automated mobile phone calls, bypassing the need for an internet connection but requiring a stable cellular signal to maintain two-way communication. Unreliable cellular access could result in systemic attrition, fragmented data collection, and compromised assessment of clinical parameters and treatment adherence. Therefore, this criterion was established to minimize technical failures and maximize the study's internal validity.

Study group allocation

A total of 121 patients were included in the prospective comparative open-label study. Participants were allocated into 2 groups according to the availability of technology and consent to participate in the remote monitoring program.

Monitoring group (main group, n=71): patients who gave informed consent to use the voice assistant. They received standard medical care in compliance with current clinical guidelines and daily RPM via the AI assistant.

Comparison group (control group, n=50): patients who received standard medical care alone (including a scheduled in-person follow-up at 1 month). This group was matched with the main group regarding baseline clinical and demographic characteristics.

All enrolled patients received standard basic therapy in accordance with current clinical guidelines for the management of T2DM and obesity. This therapy comprised non-pharmacological interventions (lifestyle modifications, including a hypocaloric diet and structured physical activity) alongside pharmacological treatment [16, 17]. Glucose-lowering therapy was prescribed and titrated by the attending physician based on individual patient parameters (HbA1c, baseline body weight, and CVC risk). Oral antihyperglycemic drugs from various classes could be used in both groups, including sulfonylureas, dipeptidyl peptidase-4 inhibitors (DPP-4i), glucagon-like peptide-1 (GLP-1) analogues, and sodium-glucose cotransporter-2 inhibitors (SGLT2i). The prescription of specific drug classes was not mandated by the study protocol and was determined solely by clinical necessity within standard medical practice.

Laboratory and instrumental examinations

At enrollment, all patients underwent comprehensive laboratory testing, including the measurement of HbA1c, fasting plasma glucose, and a lipid panel (total cholesterol, triglycerides [TG], and high-density lipoprotein cholesterol [HDL-C]). Blood samples were collected using a standardized method following a 12-hour overnight fast.

To assess the dynamics, follow-up evaluations of the lipid panel and fasting plasma glucose were performed at 1 month. Given the short duration of the follow-up period, HbA1c as an integral marker of glycemic control over the preceding 2–3 months was not reevaluated. Patients remained on their previously prescribed lipid-lowering therapy at unchanged doses throughout the entire study period; treatment regimens and dosages were verified using medical records. The obtained TG and HDL-C values were used to calculate metabolic indices (LAP index and VAI) at baseline and at 1 month.

AI-driven voice assistant RPM system

Monitoring was conducted via a fully automated system that made daily phone calls to patients within a prearranged time window. If the patient was unavailable, up to three redial attempts were performed. The RVA administered a structured questionnaire based on a predefined algorithm. Patients verbally reported their capillary blood glucose concentrations, measured via individual glucometers; a level ≥ 8.0 mmol/L triggered an automated alert to the investigator. Patients also reported their WC (cm), self-measured using a tape measure, with any increase >2 cm compared

to the previous reading flagged by the system. Binary (yes/no) questions were utilized to assess symptoms associated with hyperglycemia (polydipsia, polyuria, dry mouth) and hypoglycemia (weakness, dizziness, tremor, tachycardia). The detection of a cluster of red-flag symptoms prompted a standardized voice recommendation to seek immediate emergency medical care. Standardized voice reminders regarding medication adherence were also provided, and patients could leave a verbal question or comment for their attending physician. Upon detecting clinically significant deviations (hyperglycemia, hypoglycemia, increased WC or body weight, or reported red-flag symptoms), the system generated an automated alert for the investigator and recommended calling an ambulance. The physician then contacted the patient by phone within 24 hours for clinical evaluation and therapeutic adjustment, if necessary. Contact was also initiated if a patient failed to provide data for three consecutive days.

Outcome measures

All parameters were assessed at baseline and at 1 month of follow-up.

Primary endpoints: The absolute and relative changes in the LAP index [4] and VAI [5].

The LAP index was calculated as follows:

$$\begin{aligned} &(\text{WC [cm]} - 65) \times \text{TG [mmol/L]} \text{ for men} \\ &\text{and } (\text{WC [cm]} - 58) \times \text{TG [mmol/L]} \text{ for women.} \end{aligned}$$

The VAI was calculated using the following formula:

$$\begin{aligned} &((\text{WC [cm]} / (39.68 + (1.88 \times \text{BMI [kg/m}^2\text{]}))) \times \\ &(\text{TG [mmol/L]} / 1.03) \times (1.31 / \text{HDL-C [mmol/L]})) \\ &\quad \text{for men and} \\ &((\text{WC [cm]} / (36.58 + (1.89 \times \text{BMI [kg/m}^2\text{]}))) \times \\ &(\text{TG [mmol/L]} / 0.81) \times (1.52 / \text{HDL-C [mmol/L]})) \\ &\quad \text{for women.} \end{aligned}$$

Secondary endpoints: The absolute and relative changes in fasting plasma glucose concentration, BMI, and health-related quality of life scored via the SF-36 questionnaire. For an overall assessment, a normalized total score was utilized, calculated as the arithmetic mean of all eight questionnaire scales following their standardization and transformation into scores ranging from 0 to 100, where 100 represents the highest possible quality of life [18].

Statistical analysis

Sample size was determined based on the expected effect on the LAP index (a 20% reduction in the monitoring group), with a power of 80% and a significance level of 0.05, requiring a minimum of 50 patients per group. Statistical analysis was conducted using StatTech software, version 4.8.11 (StatTech LLC, Russia).

The normality of continuous variables was assessed using the Shapiro-Wilk test. Given the non-normal distribution of the data, continuous variables are presented as medians (Me) and interquartile ranges [Q1; Q3]. The Mann-Whitney U test was used to compare continuous variables between two independent groups. The Wilcoxon test was applied to evaluate intragroup dynamics of continuous variables. Categorical variables are expressed as absolute and relative frequencies (n, %) and were compared using Pearson's chi-squared test. Statistical significance was set at $p < 0.05$. The analysis was conducted on an intention-to-treat (ITT) basis.

Results

Baseline patient characteristics

The final analysis included data from all patients ($n=121$) who completed the study in accordance with the protocol. A comparison of baseline demographic and clinical characteristics between the monitoring group and the control group is presented in Table 1. The groups were comparable in terms of age, sex, BMI, LAP index, VAI, and quality of life (SF-36) ($p > 0.05$ for all listed parameters). The only statistically significant difference at baseline was a higher fasting plasma glucose concentration in the monitoring group compared to the control group (7.30 [6.44; 9.37] mmol/L vs. 6.60 [5.69; 7.78] mmol/L, respectively; $p=0.002$). This baseline discrepancy was adjusted for in the subsequent analysis of parameter dynamics. The groups were balanced regarding the severity of DM and the presence of complications. The sole exception was a higher prevalence of diabetic neuropathy in the monitoring group (Table 2).

Primary endpoints

The most significant effect of RPM was observed on visceral adiposity markers. The intervention group demonstrated a statistically significant reduction in the LAP index by 25.9% (from 79.36 [58.41; 112.80] to 58.80 [43.70; 70.70]; $p < 0.001$) and VAI by 31.2% (from 2.15 [1.50; 3.19] to 1.48 [1.11; 2.46]; $p < 0.001$). Conversely, no positive trend was seen in the control group: the median LAP index increased from 70.40 [46.62; 98.80] to 79.59 [56.20; 113.40] ($p=0.198$), while the change in VAI also failed to reach statistical significance ($p=0.143$; Table 3). Consequently, after 1 month of follow-up, statistically significant differences emerged between the groups in both the LAP index ($p=0.004$) and VAI ($p=0.007$). This demonstrates a targeted positive impact of RPM on the pathophysiological mechanisms of cardiometabolic risk associated with visceral adiposity.

Table 1. Baseline clinical, demographic, and anthropometric characteristics of patients in the monitoring and comparison groups

Parameter	Monitoring group (n=71)	Comparison group (n=50)	P
Age, year	65 [58.0; 70.0]	63.5 [57.0; 69.0]	0.451
Male, n (%)	32 (45.1)	25 (50.0)	0.587
BMI, kg / m ²	32 [30.0; 34.5]	32 [30.0; 35.0]	0.898
Waist circumference, cm	108.0 [98.0; 118.0]	109.0 [99.0; 119.0]	0.730
Fasting blood glucose, mmol/L	7.30 [6.44; 9.37]	6.60 [5.69; 7.78]	0.002
HbA1c, %	6.80 [6.50; 7.10]	6.90 [6.60; 7.20]	0.720
LAP index	79.36 [58.41; 112.80]	70.40 [46.62; 98.80]	0.188
VAI	2.15 [1.50; 3.19]	2.09 [1.26; 2.61]	0.320
SF-36 quality of life assessment, scores	73.0 [68.0; 77.0]	71.0 [69.0; 73.0]	0.200
Glucose-lowering therapy, n (%)			
Biguanides (metformin)	70 (98.6)	49 (98.0)	1.000
Sulfonylureas	58 (81.7)	39 (78.0)	0.649
DPP-4 inhibitors (DPP-4i)	61 (85.9)	40 (80.0)	0.459
GLP-1 receptor agonists	8 (11.3)	7 (14.0)	0.781
SGLT2 inhibitors (SGLT2i)	14 (19.7)	16 (32.0)	0.123
Concomitant therapy, n (%)			
Antihypertensive	68 (95.8)	47 (94.0)	0.690
Lipid-lowering	69 (97.2)	48 (96.0)	1.000

Data are presented as median and interquartile range (Me [Q1; Q3]) or as absolute numbers and percentages (n, %). The Mann-Whitney U test was used to compare continuous variables between independent groups. Categorical variables were analyzed using Pearson's χ^2 test; Fisher's exact test was applied when the expected cell count in any contingency table cell was less than 5. Differences were considered statistically significant at $p < 0.05$. The absence of statistically significant differences between the groups at baseline ($p > 0.05$ across all parameters, except for glucose levels) confirms group comparability. BMI, body mass index; HbA1c, glycated hemoglobin; LAP, lipid accumulation product; VAI, visceral adiposity index; SF-36, 36-item short form quality of life survey; DPP-4, dipeptidyl peptidase-4; GLP-1, glucagon-like peptide-1; SGLT2, sodium-glucose cotransporter 2.

Secondary endpoints

Glycemic control

Despite baseline fasting blood glucose levels being higher in the monitoring group, a statistically significant reduction of 15.1% was achieved by the end of the study (down to 6.20 [5.55; 7.00] mmol/L; $p < 0.001$). Conversely, no significant changes were observed in the control group ($p=0.554$). Importantly, the baseline statistically significant differences in

Table 2. Baseline patient characteristics by presence of diabetic complications

Parameter	Monitoring group (n=71)	Comparison group (n=50)	P
Diabetic nephropathy	68 (95.8)	48 (96.0)	1.000
Diabetic neuropathy	41 (57.7)	18 (36.0)	0.018
Diabetic retinopathy	47 (66.2)	31 (62.0)	0.635
Atherosclerotic vascular changes	63 (88.7)	46 (92.0)	0.759
History of ACVA	15 (21.1)	7 (14.0)	0.349
History of AMI	6 (8.5)	9 (18.0)	0.161

Data are presented as absolute numbers and group percentages (n, %). Categorical variables were compared using Pearson's χ^2 test; Fisher's exact test was applied when the expected cell count in any contingency table cell was less than 5. ACVA, acute cerebrovascular accident; AMI, acute myocardial infarction.

blood glucose levels between the groups ($p=0.002$) were neutralized by the end of the study and became non-significant ($p=0.133$). This indicates that remote monitoring provided a pronounced improvement in glycemic control among patients with higher baseline levels, whereas no substantial dynamics occurred under standard observation.

Anthropometric parameters

The monitoring group demonstrated a statistically significant, albeit clinically moderate, reduction in median BMI by 1.0 kg/m² ($p<0.001$). Conversely, no changes in BMI were observed in the control group ($p=0.922$).

Health-related quality of life

The overall SF-36 questionnaire score increased significantly in both groups after 1 month, which may be partially attributed to the non-specific effect of study participation (the so-called Hawthorne effect). However, the increase was substantially more pronounced in the monitoring group, rising by 7 points (from 73.0 [68.0; 77.0] to 80.0 [77.0; 82.0]; $p<0.001$), where-

as the median increase in the control group was only 1 point (from 71.0 [69.0; 73.0] to 72.0 [70.0; 75.0]; $p<0.001$). Intergroup differences in SF-36 scores at 1 month were statistically significant ($p<0.001$), indirectly suggesting higher treatment adherence and subjective satisfaction with the monitoring process in the monitoring group.

Treatment adherence

High patient adherence to therapy was observed in the remote monitoring group, with 29 (42.0%) patients fully complying with recommendations at the 1-month follow-up. Adherence in the comparison group was lower, with only 9 (18.0%) patients remaining compliant. These quantitative data demonstrate a statistically significant ($p<0.05$) improvement in therapy adherence metrics among patients using the AI-assisted remote monitoring system compared to those under standard observation.

Discussion

The present study confirms the efficacy of AI-powered RVA-driven RPM in modifying metabolic parameters in patients with obesity and T2DM. The most pronounced effect was observed in visceral adiposity markers, with the LAP index decreasing by 25.9% and the VAI by 31.2%. Crucially, the control group showed no improvement in these metrics, exhibiting a trend toward negative dynamics instead. These indices are composite markers that reflect visceral adipose tissue-related cardiometabolic risk more accurately than traditional anthropometric measurements such as BMI [19]. Unlike BMI, which changed negligibly in our study, the LAP index and VAI are sensitive to changes in visceral fat and its associated insulin resistance [20]. The upward trend in the LAP index observed in the control group indicates the progression of metabolic disorders under standard therapy, further validating the efficacy of the proposed intervention. Our findings align with the contemporary view of vis-

Table 3. Changes in metabolic parameters and quality of life after 1 month of follow-up

Group	Parameter	Baseline Me [Q1; Q3]	At 1 month, Me [Q1; Q3]	p (Wilcoxon criterion)
Monitoring (n=71)	LAP index	79.36 [58.41; 121.80]	58.80 [43.70; 70.70]	<0.001
	VAI	2.15 [1.54; 3.10]	1.48 [1.08; 2.18]	<0.001
	Glucose, mmol/L	7.30 [6.43; 9.20]	6.20 [5.70; 6.90]	<0.001
	Quality of life, scores	73.0 [68.0; 78.0]	80.0 [75.0; 83.0]	<0.001
Control (n=50)	LAP index	70.40 [46.62; 98.80]	79.59 [56.20; 113.40]	0.198
	VAI	2.09 [1.26; 2.62]	2.25 [1.58; 3.15]	0.143
	Glucose, mmol/L	6.60 [5.69; 7.79]	6.25 [5.70; 7.00]	0.554
	Quality of life, scores	71.0 [68.0; 74.0]	72.0 [69.0; 76.0]	<0.001

Data are presented as median and interquartile range (Me [Q1; Q3]). Between-group differences at 1-month follow-up (Mann-Whitney U test) were statistically significant for the LAP index ($p=0.004$), VAI ($p=0.007$), and SF-36 quality of life score ($p<0.001$).

ceral adiposity as a key cardiovascular risk factor that requires targeted intervention [21].

The statistically significant intergroup differences observed as early as 1-month follow-up confirm the efficacy of the proposed monitoring and therapy adjustment methodology in achieving T2DM control and weight reduction. The statistically significant 15.1% reduction in fasting blood glucose concentration in the monitoring group aligns with data from studies on digital monitoring in patients with DM [9, 10]. The substantial improvement in quality of life, as measured by the SF-36 questionnaire in the monitoring group (+7 points vs. +1 point in the control group), demonstrates the effectiveness of this approach. This is consistent with the concept that digital health solutions offering continuous support and feedback reduce disease-related anxiety, giving patients a greater sense of security and control over their condition [18]. For cardiac patients, in whom anxiety and depression serve as independent predictors of adverse outcomes, this aspect is of paramount clinical importance [22].

In conclusion, the present study demonstrates that short-term (1-month) remote monitoring utilizing an AI-powered RVA is a highly effective strategy for metabolic risk management in patients with obesity and T2DM. In our view, this rapid and comprehensive positive trend is driven by several distinct features of the implemented model. First, the voice user interface bypasses the need for advanced smartphone or application literacy, making the technology accessible to older patients. This cohort constitutes a substantial portion of the T2DM population but is frequently excluded from the digital transformation of healthcare [11]. Second, unlike passive data collection systems, our algorithm simulated a daily dialogue with a healthcare professional, creating the psychological effect of a continuous ‘virtual physician’ presence. This not only enhanced self-monitoring adherence but likely motivated stricter dietary compliance and increased physical activity, ultimately driving the pronounced impact on visceral adipose tissue metabolism [23]. Third, the algorithm identified deviations (e.g., hyperglycemia) in near-real-time, allowing physicians to adjust therapy within 24 hours rather than waiting for a scheduled visit months later. This approach prevents prolonged periods of decompensation and potentially reduces the risk of acute and chronic complications [24].

Study limitations

Despite the clinically significant positive outcomes, the present study has several limitations:

- Short-term follow-up period: The trial lasted only 1 month, which precludes an assessment of the long-term efficacy and sustainability of the achieved modifications in metabolic parameters and quality of life;
- single-center design: The study was conducted at a single hospital, which may restrict the generalizability of the findings and their extrapolation to other patient populations and clinical care settings;
- baseline glycemic imbalance: Despite statistical adjustments, the significantly higher baseline blood glucose levels in the monitoring group could have influenced the magnitude of the observed effect;
- absence of HbA1c assessment: The protocol did not include a 1-month post-baseline measurement of glycated hemoglobin (HbA1c), which remains the ‘gold standard’ for evaluating glycemic control over a 3-month window.
- selection bias: The strict exclusion criteria (e.g., absence of psychiatric disorders, stable cellular connectivity) may limit the applicability of this approach in broader patient populations, such as those experiencing cognitive decline or lacking technical literacy.

Importantly, the system operated in strict compliance with current Russian healthcare legislation (Federal Law No. 323). It did not substitute the initial clinical examination or primary diagnosis; rather, its application provided the subsequent remote monitoring and therapy titration of patients with confirmed T2DM. This framework represents a legally authorized and structurally regulated modality of telemedicine delivery [25].

To validate and expand upon these findings, further research is required, including prospective, multi-center, randomized controlled trials with a 6-to-12-month follow-up period. It is essential to incorporate a mandatory assessment of HbA1c dynamics and, longitudinally, the tracking of hard clinical endpoints (cardiovascular complications). Additionally, evaluating the cost-effectiveness and organizational aspects of integrating such systems into routine clinical practice will be critical for large-scale implementation.

Conclusion

In conclusion, the deployment of a remote patient monitoring program utilizing an AI-powered voice assistant represents an effective, accessible, and personalized strategy for improving metabolic control, mitigating the risk of cardiometabolic complications, and enhancing the quality of life in patients with type 2 diabetes mellitus and obesity. This approach is particu-

larly critical given the escalating prevalence of these conditions and the urgent need to optimize health-care resources.

However, to confirm the sustainability of these observed effects and evaluate their long-term impact on hard endpoints (cardiovascular complications and mortality), further multi-center research with extended follow-up periods is necessary.

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