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ORIGINAL CONTRIBUTIONS

Simulation of Appointment Scheduling Policies: a Study in a Bariatric Clinic

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Abstract

Purpose Appointment scheduling systems traditionally book patients at fixed intervals, without taking into account the complexity factors of the health system. This paper analyzes several appointment scheduling policies of the literature and proposes the most suitable to a bariatric surgery clinic, considering the following complexity factors: (i) stochastic service times, (ii) patient unpunctuality, (iii) service interruptions, and (iv) patient no-shows.

Materials and Methods We conducted the study using data collected in a bariatric surgery clinic located in Rio de Janeiro, Brazil. The dataset presented 1468 appointments from June 29, 2015, to June 29, 2016. We comparatively evaluate the main literature policies through a discrete event simulation (DES).

Results The proposed policy (IICR) provides a 30% increase in attendance and allows a decrease in the total cost, maintaining the level of service in terms of average waiting time.

Conclusion IICR was successfully implemented, and the practical results were very close to the simulated ones.

Keywords Appointment scheduling · Computer simulation · Health care sector · Bariatric clinic · Operations management

Introduction

Appointment scheduling systems are developed to assign date and time for the patient arrival in a healthcare unit. The goal of a well-designed system is to find a balance between the competing goals of increasing resource utilization and reducing patient waiting time [1–3].

In order to create an appropriate appointment scheduling system, it is necessary to consider the factors that affect scheduling efficiency, such as stochastic service times, patient unpunctuality, no-show rate [1, 2, 4–6], and service interruptions [5–7]. The influence of those factors requires a continual evaluation of the scheduling systems.

Appointments are usually scheduled at fixed time intervals, without taking into account the disturbing factors discussed

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above. An efficient scheduling that considers those factors can improve the level of service and increase the provider utilization.

The development of an appointment scheduling policy can be separated into a series of decisions that involves (i) appointment scheduling rules and (ii) adjustments to reduce the deteriorating effect of no-shows [2].

Figure 1 shows the brief explanation of each appointment scheduling rule that will be tested in this paper. The rules individual block fixed interval (IBFI), two at the beginning (2BEG), OFFSET, and DOME are the best-performing policies in the literature [8], and PLATEAU-DOME [9], UNIVERSAL DOME [3], and increasing interval clustering rule (IICR) [7] are recently proposed successful policies.

An appointment scheduling policy should anticipate the effects of no-shows in order to reduce their negative impact. We used overbooking to mitigate the effect of no-shows. There are two ways of managing overbooking: (i) booking more than one patient per slot or (ii) decreasing scheduling intervals in order to increase the number of patients scheduled [2]. We used the second approach based on recent studies [3, 7, 10, 11] that showed an improvement on provider utilization.

The literature on appointments in bariatric surgery has focused on analyzing which demographic factors [12–17] and scheduling information influenced patient no-shows [17]. The focus of this paper is on the process of appointment scheduling in a bariatric clinic. The current policy schedules patients at fixed time intervals and does not consider the complexity factors of the system. Our main goal is to analyze the appointment scheduling policies of the literature and propose the best one for the bariatric surgery clinic, considering the following complexity factors: (i) stochastic service times, (ii) patient unpunctuality, (iii) service interruptions, and (iv) patient no-show. To the best of our knowledge, there is no study that presents a system considering these environment factors together. We comparatively evaluate the main literature policies through a discrete event simulation (DES). Each policy combines an appointment scheduling rule with the overbooking approach [11].

Materials and Methods

We collected data from a bariatric clinic located in Rio de Janeiro, Brazil. The authors decided to carry out the study in the consultation process of the main physician. The consultations are done before and after the bariatric surgery, and do not include the surgery itself.

Data regarding show/no-show, scheduled time, and start and end times were collected from the clinic's management information system. The dataset presented 1468 appointments from June 29, 2015, to June 29, 2016.

The process has some differences regarding the type of appointment. There are two classes of patients: (i) first appointment (new patient) and (ii) return. We can further divide the return patients into three subclasses: (i) before-surgery return, (ii) pre-surgery return (last consultation before surgery), and (iii) post-surgery return. Supplementary Material 1 illustrates the process of the clinic.

After analyzing the data, we identified the complexity factors of the system. We selected the probability distributions via the Kolmogorov-Smirnov test ($\alpha = 5\%$).

The distribution of patient unpunctuality was normal (μ=−11.7, σ=29.6 min), which shows that the patients arrive earlier on average, but there is a high variability in this process. This variability pattern adversely interferes with the performance of the system and is consistent with other related articles [8, 18]. The distribution of service interruptions was Weibull

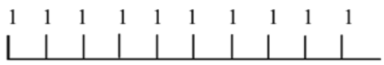
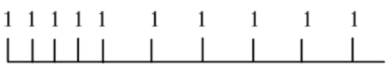
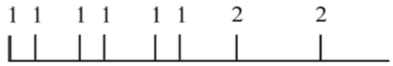
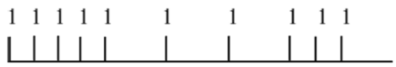
Rule	Description	Behavior
IBFI	Book patients individually at intervals equal to the mean service time.	
2BEG	Same as IBFI, with initial block of two patients.	
OFFSET	Book the first patients between shorter intervals and the last patients between longer intervals, when compared to IBFI.	
IICR	Book patients alternating shorter and longer intervals, and, from the middle to the end of the section, doublebooking occurs, with time intervals being equal to twice the mean service time.	
DOME; PLATO-DOME; UNIVERSAL DOME	Book the first patients between shorter intervals, mid-shift patients between longer intervals, and the last patients between shorter intervals, when compared to IBFI.	

Fig. 1 Appointment scheduling rules tested in this paper. Source: adapted from Cayirli et al. [3, 8] and Klassen and Yoogalingam [7, 9]

(μ=5.6, σ=4.9 min), and it occurred after 26.8% of the consultations. The interruption is caused by a provider stopping after finishing a service (e.g., to answer a call or reply an e-mail). Regarding patients' no-show, a statistical analysis through the chi-square test ($\alpha = 5\%$) was performed to determine whether non-attendance fluctuated between days of the week, daytime hours, and appointment types. Only the no-show difference between patient types was significant: 30.4% for new patients, and 19.6%, 21.0%, and 25.8% for before-surgery, pre-surgery, and post-surgery returns, respectively. The average no-show rate was 26.1%. Each patient class has a different schedule ratio and a different distribution for the provider service time, as presented in Table 1.

The method used to represent the process of the clinic was the discrete events simulation (DES) using ProModel®, version 8.6. In order to increase the reliability of the model, each simulation was replicated 500 times. In the current appointment rule (CURRENT), all patients are scheduled in 20-min slots, except pre-surgery returns, which are scheduled in 10-min slots. The patients are booked from 9:00 to 11:40 a.m. and from 1:40 to 6:00 p.m.

We ran the simulation model using the characteristics described. The validation of the results (in terms of waiting time, idle time, and overtime) was developed through a chi-square test ($\alpha = 5\,\%$). The tests showed no difference between the simulated and empirical results, validating our simulation model. Next, the following appointment scheduling policies were tested: CURRENT, IBFI, 2BEG, OFFSET (two settings), DOME, PLATEAU-DOME (three settings), UNIVERSAL DOME, and IICR. For the overbooking strategy, we used the approach based on decreasing scheduling intervals according to the no-show rate in order to increase the number of patients scheduled, proposed by LaGanga and Lawrence [10]. The details and settings of each appointment scheduling rule and of the overbooking strategy are presented in Supplementary Material 2.

Four scenarios were analyzed, as presented in Table 2. Scenario 1 is the current one (baseline). Scenario 2 is the baseline including overbooking (proposed scenario). Scenarios 3 and 4 make sensitivity analyses with different no-show levels: low no-show (20% decrease) and high no-show (20% increase).

For scenario 1, all scheduling policies were tested, with the exception of UNIVERSAL DOME, since this rule considers overbooking. For scenarios 2, 3, and 4, all policies were tested.

Table 2 Complexity factor settings of each scenario

Complexity factors/scenarios	1	2	3	4
Number of patients per section	23	30	30	30
Overbooking	No	Yes	Yes	Yes
Patient no-show	Current	Current	High	Low

The performance indicators include the patients' mean waiting time (WAIT), the provider's mean idle time per patient (IDLE), and the provider's mean overtime per patient (OVER). The waiting time for a scheduled patient is the difference between the time when consultation starts and the appointment time. Idle time is the time that the provider is idle during the session, and overtime is the extra time required to serve all patients. IDLE is calculated by dividing the total idle time by the number of patients seen. OVER is calculated by dividing the total overtime by the number of patients seen.

In order to measure the total cost of the system per patient (TC), we can also evaluate the cost of patient waiting time (Cp), provider idle time (Cd), and provider overtime (Co). We assume that Co is 50% higher than Cd (Co/Cd = 1.5), which is consistent with the literature [3, 8, 9, 11, 18]. Therefore, TC is represented as follows:

$$\mathrm{TC} = (\mathrm{WAIT})\mathrm{Cp} + [(\mathrm{IDLE}) + 1.5(\mathrm{OVER})]\mathrm{Cd} \quad (1)$$

In our study, we use the relative cost ratios (Cd/Cp), referred to as CR, in the range of 1 to 50, which provides a reasonable coverage of possible ratios between provider and patient costs. For instance, a CR equal to 1 means that the cost of the provider time is equal to the cost of the patient time, and a CR equal to 50 means that the provider cost is 50 times larger than the patient cost. It is important to analyze such a range because it is very difficult to find the exact cost of patient waiting time.

We want to know which policies are efficient for each scenario and, then, look at TC for these policies. Efficient policies are those that present the best combinations of WAIT and IDLE&OVER. In an effort to combine the two provider-related measures, we use IDLE&OVER as the sum of IDLE and 1.5 OVER.

Table 1 Schedule ratio and probability distribution of service time for each patient class

Complexity factor	Schedule ratio	Patient class	Distribution (mean, deviation) (min.)
Provider service time	51.8%	New patient	Weibull (22.3, 9.3)
	29.3%	Before-surgery return	Weibull (15.3, 8.4)
	14.4%	Post-surgery return	Weibull (15.3, 8.4)
	4.5%	Pre-surgery return	Lognormal (11.7, 6.3)

Results

In this section, we present the results of the scenarios tested. The complete results of the appointment scheduling policies in terms of WAIT, IDLE, OVER, and IDLE&OVER are shown in Supplementary Material 3.

In order to compare the policies and find which one is efficient for the proposed scenario, we can analyze their patterns in terms of WAIT versus IDLE&OVER, as shown in Fig. 2. We can see that IICR had the lowest IDLE&OVER (4.69 min) and the highest WAIT (23.17 min), being an option to increase resource utilization. On the other hand, OFFSET 2 had the lowest WAIT (17.13 min) and the highest IDLE&OVER (7.29 min), being an option to improve the level of service provided. PLATEAU-DOME 1 was also an option to improve the level of service, presenting WAIT and IDLE&OVER equal to 17.89 min and 6.69 min, respectively. Other efficient policies were PLATEAU-DOME 3, OFFSET 1, and UNIVERSAL DOME.

In order to compare the main scheduling policies of the literature, the TC of each policy was calculated for each scenario, ranging CR from 1 to 50. The results for the baseline and the proposed scenario are presented in Table 3. We can note from the results that the decision of best policy depends on the CR. In the proposed scenario, PLATEAU-DOME 1 presented the best result for CR = 1, and IICR presented the best result for CR ≥ 10.

We can see that the TC of the efficient policies analyzed decreased for all CRs (except for CR = 1). For CR ≥ 10, the best policy of the proposed scenario (IICR) allowed a decrease by at least 45% in TC compared to the CURRENT policy in the baseline scenario, while increasing the number of patients seen by 30%. We also observed that the performance of the best policies becomes more noticeable as the CR increases.

Table 4 shows the proposed appointment scheduling policies according to the CR and to the no-show rate. The current no-show is the actual no-show rate of the clinic, and the low and high rates represent the sensitivity analysis scenarios. We can observe that the dominant policy for each CR behaved well for different no-show rates. For low CR, PLATEAU-DOME 1 is the best choice. For moderate and high CR, IICR becomes the best choice.

Regarding the patient time, WAIT for IICR and PLATEAU-DOME 1 were 23.17 and 17.89 min in the proposed scenario, respectively, compared to 8.53 min for CURRENT in the baseline scenario. Regarding provider time, IICR and PLATEAU-DOME 1 showed in the proposed scenario IDLE&OVER equal to 4.69 and 6.69 min, respectively, compared to 11.88 min for CURRENT in the baseline scenario (only composed of idle time).

Conclusion

We can conclude that the proposed scenario with overbooking provides a 30% increase in attendance. Moreover, the best policy of the proposed scenario (IICR) also allows a decrease in TC by at least 45% (for CR ≥ 10), compared to the CURRENT policy in the baseline scenario, and maintains a low WAIT (23.17 min). A waiting time up to 30 min is a good measure compared to the standard established by some European countries [2]. Only for CR = 1, the best policy (PLATEAU-DOME 1) showed a TC worse than that obtained by CURRENT in the baseline scenario. We can see that IDLE decreased in the proposed scenario compared to the baseline. This shows that overbooking is important to compensate the no-show effect.

We also analyzed the proposed policies according to CR and to the no-show rate. For low CR, PLATEAU-DOME 1 is the best choice and, for moderate and high CRs, IICR is the overall best choice (Table 4). IICR is the best choice for high CRs because it favors the provider time instead of the patient

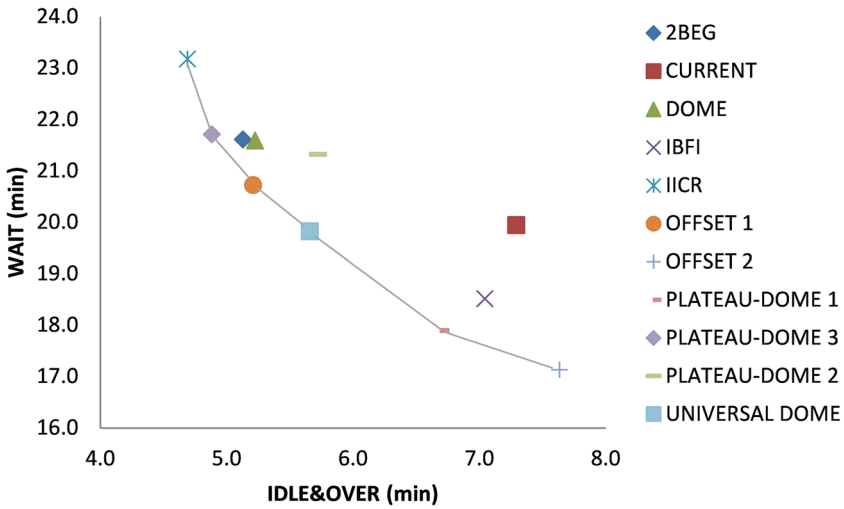


Fig. 2 Efficient policies for the proposed scenario

Table 3 Comparison of the appointment scheduling policies

Scenario	Patients seen	Appointment scheduling rule	TC (CR = 1)	TC (CR = 10)	TC (CR = 25)	TC (CR = 40)	TC (CR = 50)
Baseline	17	2BEG	20.79	114.60*	270.94*	427.28*	531.50*
		DOME	19.56*	115.08	274.28	433.48	539.62
		PLATEAU-DOME 2	19.33*	116.03	277.18	438.34	545.77
		IBFI	19.23*	123.12	296.26	469.40	584.83
		PLATEAU-DOME 1	19.26*	125.19	301.73	478.27	595.97
		CURRENT	20.41	127.34	305.55	483.76	602.56
Proposed	22	IICR	27.86	70.09*	140.47*	210.85*	257.77*
		PLATEAU-DOME 3	26.60	70.57*	143.85	217.13	265.99
		OFFSET 1	25.93	72.81	150.95	229.09	281.18
		UNIVERSAL DOME	25.48	76.42	161.31	246.20	302.80
		PLATEAU-DOME 1	24.58*	84.82	185.22	285.61	352.54
		OFFSET 2	24.77*	93.49	208.04	322.58	398.94
		CURRENT	27.23	92.86	202.25	311.64	384.56

*Best policies for each cost ratio

time, and PLATEAU-DOME 1 is the best choice for low CR because it favors the patient time (Fig. 2). In the context of the clinic analyzed, we recommended the use of IICR as the new scheduling policy, because we assumed that the provider cost is at least 10 times higher than the patient cost (CR ≥ 10). The policy was successfully implemented, and the obtained results were very close to the simulated ones. The number of services increased by 30%, and the level of service remained high (mean waiting time lower than 30 min). We included the implemented schedule of IICR in the Supplementary Material 4.

Prior studies [1, 3, 5–9, 11, 18] have considered different methodologies and complexity factors to find the best policy and, with few exceptions [1, 8, 18], all found DOME or PLATEAU-DOME rules to be the best. Klassen and Yoogalingam [7] showed that patient unpunctuality is a factor that makes a difference in terms of which appointment policy is the best. Their study found that, when the patient unpunctuality is considered, the IICR rule can improve system performance compared to other rules (e.g., PLATEAU-DOME and DOME), which is consistent with our results. We also considered the patient unpunctuality in our work, and this is one of the reasons for IICR to be the best. This policy alternates between long and short intervals, and, as the session progresses, it benefits from an increasing difference between these long and short appointment slots, such that it uses double-booking and triple-booking.

The average no-show rate was 26.1%, which is higher than the average found in a recent systematic literature review (23.0%) that analyzed 105 papers dealing with determinants of no-show in appointment scheduling [19]. After compensating this factor using the overbooking rule, we noted an improvement of 30% in attendance. Therefore, we can observe that it is important to consider the no-show rate when designing an appointment scheduling policy. Klassen and Yoogalingam [7] noted that, although no-shows negatively impact performance, they do not impact which overall scheduling policy is best, which was also noted in our sensitivity analysis: the best policy of the proposed scenario (IICR) remained the best even after decreasing and increasing the no-show rate by 20% (scenarios 3 and 4).

The major contribution of this study was twofold: to analyze several appointment scheduling policies of the literature and to propose the best one for the bariatric clinic, improving its revenue and maintaining the level of service provided. Another relevant aspect is the number of complexity factors considered: unpunctual patients, presence of no-shows per type of appointment, stochastic service times, and service interruptions. To the best of our knowledge and according to the

Table 4 Choosing the best policy

Cost ratio (CR)	No-show rate	Proposed appointment scheduling policy
Low (CR = 1)	Low	PLATEAU-DOME 1
	Current	PLATEAU-DOME 1 (or OFFSET 2)
	High	PLATEAU-DOME 1
High (CR ≥ 10)	Low	IICR
	Current	IICR
	High	IICR

papers reviewed by Ahmadi-Javid et al. [20], there is no study that presents a system considering all these environment factors together.

Regarding the scheduling process, one relevant aspect is that the proposed schedule determines only the appointment times and does not have pre-allocated slots for specific types of patients. Therefore, any patient can be scheduled in any available appointment time, which makes the schedule flexible for patients experiencing complications. The proposed process of scheduling works as follows. First, the surgeon decides in which week the patient should be back (for return patients). Second, the administrative staff presents to the patient (either new or return) the available slots in each day of that week based on our proposed schedule, and the patient chooses the more suitable appointment time. The surgeon's scheduling decision considers the patient's clinical information collected by a multidisciplinary team and has the potential to give a closer follow-up in patients exhibiting more comorbidities (i.e., type 2 diabetes mellitus, cardiovascular diseases, etc.), which is important in order to check them as well as to adapt the amount of drugs needed by the patient after surgery. Some relevant clinical information is related to underlying molecular aspects that can affect the changes following comorbidity resolution after surgery (i.e., influence of leptin [21], caveolin-1 [22], serum amyloid A [23], and FGFs [24] on cardiometabolic control together with their supporting references).

In this study, we aimed to propose an appointment schedule for the main surgeon of the clinic. This schedule pertains only to him and cannot be used by any other surgeon or physician in the clinic. We chose the main surgeon because he has the greatest demand of patients. For future work, we want to propose appointment schedules for the other surgeons, endocrinologists, internists, and nutritionists who have great demand of patients in the clinic. We also want to replicate this work in other bariatric clinics in order to improve their revenue and level of service, as well as to see whether the results will converge for the same best rules.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors. For this type of study, formal consent is not required.

References

1. Bhattacharjee P, Ray PK. Simulation modelling and analysis of appointment system performance for multiple classes of patients in a hospital: a case study. Oper Res Health Care. 2016;8:71–84.
2. Cayirli T, Veral E. Outpatient scheduling in health care: a review of literature. Prod Oper Manag. 2003;12(4):519–49.
3. Cayirli T, Yang KK, Quek SA. A Universal appointment rule in the presence of no-shows and walk-ins. Prod Oper Manag. 2012;21(4):682–97.
4. Gupta D, Denton B. Appointment scheduling in health care: challenges and opportunities. IIE Trans. 2008;40(9):800–19.
5. Salzarulo PA, Bretthauer KM, Côté MJ, et al. The impact of variability and patient information on health care system performance. Prod Oper Manag. 2011;20(6):848–59.
6. Klassen KJ, Yoogalingam R. Appointment system design with interruptions and physician lateness. Int J Oper Prod Manag. 2013;33(4):394–414.
7. Klassen KJ, Yoogalingam R. Strategies for appointment policy design with patient unpunctuality. Decis Sci. 2014;45(5):881–911.
8. Cayirli T, Veral E, Rosen H. Designing appointment scheduling systems for ambulatory care services. Health Care Manag Sci. 2006;9(1):47–58.
9. Klassen KJ, Yoogalingam R. Improving performance in outpatient appointment services with a simulation optimization approach. Prod Oper Manag. 2009;18(4):447–58.
10. LaGanga LR, Lawrence SR. Clinic overbooking to improve patient access and increase provider productivity*. Decis Sci. 2007;38(2):251–76.
11. Cayirli T, Yang KK. A Universal appointment rule with patient classification for service times, no-shows, and walk-ins. Serv Sci. 2014;6(4):274–95.
12. Spaniolas K, Kasten KR, Celio A, et al. Postoperative follow-up after bariatric surgery: effect on weight loss. Obes Surg. 2016;26(4):900–3.
13. Wheeler E, Prettyman A, Lenhard MJ, et al. Adherence to outpatient program postoperative appointments after bariatric surgery. Surg Obes Relat Dis. 2008;4(4):515–20.
14. Sockalingam S, Cassin S, Hawa R, et al. Predictors of post-bariatric surgery appointment attendance: the role of relationship style. Obes Surg. 2013;23(12):2026–32.
15. Toussi R, Fujioka K, Coleman KJ. Pre- and postsurgery behavioral compliance, patient health, and postbariatric surgical weight loss. Obesity (Silver Spring). 2009;17(5):996–1002.
16. Pontiroli AE, Fossati A, Vedani P, et al. Post-surgery adherence to scheduled visits and compliance, more than personality disorders, predict outcome of bariatric restrictive surgery in morbidly obese patients. Obes Surg. 2007;17(11):1492–7.
17. Dantas LF, Hamacher S, Cyrino Oliveira FL, et al. Predicting patient no-show behavior: a study in a bariatric clinic. Obes Surg. 2019;29(1):40–7.
18. Cayirli T, Veral E, Rosen H. Assessment of patient classification in appointment system design. Prod Oper Manag. 2008;17(3):338–53.
19. Dantas LF, Fleck JL, Cyrino Oliveira FL, et al. No-shows in appointment scheduling – a systematic literature review. Health Policy. 2018;122(4):412–21.
20. Ahmadi-Javid A, Jalali Z, Klassen KJ. Outpatient appointment systems in healthcare: a review of optimization studies. Eur J Oper Res. 2017;258(1):3–34.

21. Gómez-Ambrosi J, Salvador J, Páramo JA, et al. Involvement of leptin in the association between percentage of body fat and cardiovascular risk factors. Clin Biochem. 2002;35(4):315–20.
22. Catalán V, Gómez-Ambrosi J, Rodríguez A, et al. Expression of caveolin-1 in human adipose tissue is upregulated in obesity and obesity-associated type 2 diabetes mellitus and related to inflammation. Clin Endocrinol. 2008;68(2):213–9.
23. Gómez-Ambrosi J, Salvador J, Rotellar F, et al. Increased serum amyloid a concentrations in morbid obesity decrease after gastric bypass. Obes Surg. 2006;16(3):262–9.
24. Gallego-Escuredo JM, Gómez-Ambrosi J, Catalan V, et al. Opposite alterations in FGF21 and FGF19 levels and disturbed expression of the receptor machinery for endocrine FGFs in obese patients. Int J Obes. 2015;39(1):121–9.