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Original Article

Effectiveness of artificial intelligent cardiac remote monitoring system for evaluating asymptomatic myocardial ischemia in patients with coronary heart disease

Bin Jiang[1], Nengbin Dong[1], Jinliang Shou[1], Limei Cao[2], Kai Hu[1], Wencheng Liu[3], Xia Qi[3]

[1]Functional Examination Center, [2]Department of Neurology, The First People's Hospital of Chenzhou City, Chenzhou 423000, Hu'nan Province, China; [3]Department of Research & Development, Lepu Medical Technology (Beijing) Co., Ltd., Beijing 102200, China

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Abstract: Objective: To explore the effectiveness of cardiac remote monitoring system (CRMS) based on artificial intelligence-enabled ECG algorithm mode for evaluating asymptomatic myocardial ischemia (AMI) in patients with coronary artery disease (CAD). Methods: Two hundred CAD patients confirmed by coronary angiography (CA) in our hospital were included as the study subjects, 120 of whom developed myocardial ischemia (MI). All patients received 12-lead telephone remote ECG monitoring and evaluation. After monitoring, artificial intelligence-enabled ECG algorithm was performed to observe the detection rate of MI. Results: Compared with artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system, the detection rate of remote ECG monitoring system in 120 MI patients was lower (96.67% vs. 86.67%, P<0.01). Among the 120 MI patients, there were 26 patients (21.67%) with symptomatic myocardial ischemia (SMI) and 94 patients (78.33%) with AMI. There was no difference between the two detection methods in the diagnosis of SMI (P>0.05), while there was a difference in the diagnosis of AMI (P<0.01). The degree and duration of ST segment decline and the threshold variability of MI were higher in SMI patients than those in AMI patients (P<0.001). It showed that the lowest frequency of MI was from 0:00 to 06:00, and the highest from 06:01 to 12:00, with significant difference compared with other time periods (P<0.05). Conclusion: The CRMS based on artificial intelligence-enabled ECG algorithm mode can significantly improve the detection rate of AMI. Moreover, small changes of ST segment in AMI patients and circadian rhythm of disease onset were presented.

Keywords: Coronary artery disease, asymptomatic myocardial ischemia, remote cardiac monitoring, artificial intelligence-enabled ECG algorithm, evaluation of effectiveness

Introduction

Coronary artery disease (CAD) is a common disease in elderly patients, whose morbidity and mortality are increasing year by year. The morbidity of Chinese residents is about 0.77-1.24%, which appears to be higher in elderly patients. In China, the mortality of CAD in urban population is 107.5/100,000, higher than that in rural population of 105.37/100,000 [1]. The clinical manifestations of CAD are chest tightness and chest pain, but no typical clinical symptoms were found in some patients [2]. Myocardial ischemia (MI) confirmed only through clinical examination is called asymptomatic myocardial ischemia (AMI). Due to insidious and difficult to be detected onset of AMI, the mortality of AMI patients is significantly higher than that of symptomatic patients [3]. ECG is the main method to monitor MI; however, short recording time of conventional ECG is prone to miss diagnosis of the occurrence of MI [2]. Cardiac remote monitoring system (CRMS) is a remote monitoring system for CAD patients with ECG monitoring devices. Abnormal ECG information can be quickly and remotely exchanged through modern communication facilities with no time or region limit, which is conducive to timely diagnosis and treatment by doctors and experts [4]. Although remote ECG monitoring solves the problem of short ECG recording time and is beneficial to clinical monitoring and early diagnosis, it still has relatively low automatic diagnosis rate and accuracy, about 50-60% [5-7]. With the development of computer intelligence technology, artificial intelligence-enabled ECG algorithm has made great progress in the diagnosis of heart disease, and it has been involved in the diagnosis and treatment of CAD [8]. Studies have confirmed that compared with the traditional ECG mode, artificial intelligence-enabled ECG can improve the detection rate of patients with undiagnosed cardiac arrhythmia [9]. However, there are few literatures on the detection of AMI through intelligence-enabled ECG combined with CRMS. This study takes this as an innovation point and uses artificial intelligence-enabled ECG algorithm to evaluate the clinical effectiveness in treating MI patients on the basis of CRMS.

Materials and methods

Clinical information

Approved by the ethics committee of our hospital, this retrospective study included 200 patients diagnosed with CAD admitted to our hospital from May 2018 to May 2020 as research subjects. The included patients aged from 42-73 years, with an average age of 52.4±9.3 years, including 124 males and 76 females. And MI occurred in 120 patients during the monitoring period.

Inclusion criteria: (1) Patients who met the diagnostic criteria for CAD proposed by the Chinese Medical Association and underwent coronary angiography [10]; (2) Patients with clear consciousness and free speech capability; (3) Patients with complete clinical data.

Exclusion criteria: (1) Patients with contraindication to 12-lead telephone remote ECG monitoring; (2) Patients with cardiomyopathy, ventricular hypertrophy, conduction block or preexcitation syndrome that might affect ST segment changes; (3) Patients with cognitive insufficiency or language barrier; (4) Pregnant and lactating women.

Methods

CRMS: First of all, all patients received 12-lead telephone remote ECG monitoring (Shandong Kang You Medical Technology Co., Ltd., Chins), with continuous monitoring for 3 d. The 12-lead ECG of patients was recorded, as well as the related symptoms and life logs. GPRS was applied to collate the collected data, and the models of automatic alarm, sending, asking for help, expert processing and electrode dropping alarm were used to observe the ECG dynamics throughout the day. The system alarmed for abnormal ECG itself or patients alerted the medical staff when they had symptoms. Professional personnel carried on early warning to heart disease in real time. In case of ECG abnormality, ECG professionals on the ECG monitoring platform of our hospital would send short messages to the patients to inform the experts' treatment suggestions, or communicate with them by telephone to explain the treatment methods. After the completed monitoring, the data from the warning device would be exported through USB for collation and analysis [5].

Artificial intelligence-enabled ECG algorithm: In the remote ECG monitoring system, the patient's 12-lead ECG as well as its related symptoms and life logs were recorded. The data were processed using artificial intelligence ECG analysis software [9].

Positive diagnostic criteria: Two physicians diagnosed the patients' MI state according to the ECG. If they gave consistent diagnosis, it was regarded as the positive diagnostic criteria. If not, it was submitted to the third clinical expert for review, and the consistent results of the three clinical experts were taken as the positive diagnostic criteria. The diagnostic criteria of MI were as follows: (1) Taking the baseline of the equipotential line as the reference, the ST segment was downward inclined or horizontal, and the downward shift amplitude was equal or over 0.1 mV. (2) Duration of downward movement was equal or over 1 min. (3) The time interval between the two MI attacks was equal or over 1 min and the ST segment was measured at 80 ms behind J point.

Outcome measures

(1) The number of CAD patients who had MI during the monitoring period was recorded. (2) The detection rate of MI was compared between remote ECG monitoring system and artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system. Detection rate = (number of actual cases detected/total cases occurred) × 100%. (3) The detection rate

Table 1. General information of 120 patients with MI during remote monitoring ($\overline{x}$±sd)

Item	MI occurred during remote monitoring (n=120)
Average age (years)	51.6±9.3
Gender (male/female)	84/36
BMI (kg/m^2)	25.14±2.33
Combined disease (n)	
Hypertension	65
Hyperlipemia	21
Type 2 diabetes	70
Smoking	96
Number of stenosed coronary vessel (n)	
Single vessel	19
Double vessel	43
Triple vessel	58
Degree of coronary artery stenosis (n)	
Mild stenosis (<50%)	14
Mitral stenosis (50%~75%)	37
Severe stenosis (>75%)	69

Note: MI: myocardial ischemia.

of symptomatic and asymptomatic patients with MI was compared between remote ECG monitoring system and artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system. Detection rate = (number of actual cases detected/total cases occurred) × 100%. (4) The general information, the occurrence time of MI, the range and duration of ST segment decline, and the threshold variability of MI in the SMI and AMI patients were compared. The threshold variability of MI = (the highest MI threshold - the lowest MI threshold)/the lowest MI threshold × 100%.

Statistical analysis

SPSS 23.0 statistical software was used to analyze the data. Continuous variables were represented as mean ± standard deviation ($\overline{x}$ ±sd), and data with normal distribution and homogeneity of variance were tested by independent samples t test. Count data were represented as number of cases and percentage, and analyzed by paired χ^2 test. P<0.05 indicates a significant difference.

Results

General information

Among the included 200 patients, 120 cases developed MI symptoms during remote monitoring, with an incidence rate of 60%. The general data of 120 patients were collected and analyzed. See **Table 1**.

Detection rate of MI by two monitoring methods

Two detection methods were used to monitor the incidence of MI. The detection rate of remote ECG monitoring system for 120 patients with MI was 86.67%, which was lower than that of artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system (96.67%, P<0.01). See **Table 2** and **Figure 1**.

Detection rate of artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system in SMI and AMI patients

Among 120 patients, there were 26 patients (21.67%) with SMI and 94 patients (78.33%) with AMI. No difference between the two detection methods in the diagnosis of SMI was found (P>0.05, **Table 3**). However, there was a difference between the two detection methods in the diagnosis of AMI (P<0.01, **Table 4** and **Figure 2**). It is suggested that artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system improved the detection rate of AMI patients.

Comparison of general information in SMI and AMI patients

The general information of SMI and AMI patients was further compared. It was found that there was no statistical difference in the general information of SMI and AMI patients (P>0.05), including age, gender, BMI, combined disease, number of diseased coronary vessels, and degree of coronary artery stenosis. See **Table 5**.

Comparison of attacks in SMI and AMI patients

The degree of ST segment decline, the duration of ST segment decline and the threshold variability of MI in SMI patients were higher than those in AMI patients (P<0.001). See **Table 6**.

Table 2. Detection rate of MI by two monitoring methods (n, %)

Group	Positive	Negative
Remote ECG monitoring system (n=120)	104 (86.67)	16 (13.33)
Artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system (n=120)	116 (96.67)	4 (3.33)
χ^2	7.822	
P	0.005	

Note: MI: myocardial ischemia.

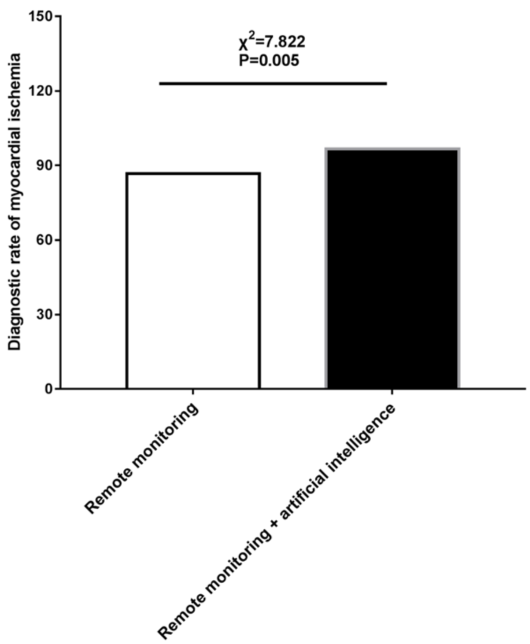

Figure 1. Comparison of the detection rate of MI between the two monitoring methods. MI: myocardial ischemia.

Comparison of onset time in SMI and AMI patients

A total of 478 times of MI occurred in the included patients, including 80 times in SMI patients and 398 times in AMI patients. There was no difference in the frequency of MI between SMI and AMI patients at different time periods (P>0.05). Further studies showed that the frequency of MI was the lowest from 0:00 to 06:00, while highest from 06:01 to 12:00, which was statistically different from other time periods (P<0.05). See in **Table 7**.

Discussion

According to China Cardiovascular Disease Report 2018, nearly half of the 290 million patients with cardiovascular diseases died, and the fatality rate was much higher than that of malignant tumors and other diseases. Therefore, improving early diagnosis of disease and timely treatment play an important role in improving survival rate [11, 12]. MI is the cause of a variety of heart diseases, especially for CAD. However, there is no significant ST segment change in ECG detection of some patients in the outpatient department, which increases the rate of missed diagnosis and the risk of death in cardiovascular patients.

The occurrence and development of AMI is related to the insufficiency of coronary artery blood supply. The onset of AMI is difficult to be detected, and may lead to sudden death, acute myocardial infarction and other serious adverse coronary events in CAD patients. The pathogenesis of AMI is related to multiple mechanisms [13]. The possible reasons of low detection rate of remote ECG monitoring to diagnose AMI are as follows. Due to the short duration of AMI in patients, low change range of ST segment, and interference from daily activities, remote ECG monitoring reduces the diagnostic rate of AMI, while artificial intelligence can effectively eliminate the above interferences to achieve accurate diagnosis [14]. This study confirmed that cardiac remote monitoring based on artificial intelligence-enabled ECG algorithm could significantly improve the diagnostic rate of AMI patients. However, the artificial intelligence-enabled ECG algorithm combined with remote cardiac monitoring in partial MI patients has relatively low detection rate. It may be related to the fact that some MI patients who already have coronary artery lesions and stenosis have no ST segment changes, the scope of coronary artery stenosis is small, and EGG in the ischemic part of myocardium is changed [15].

Remote heart detection technology adopts modern advanced technology to collect ECG data from MI patients and transmit it to the ECG center for real-time diagnosis, risk assessment and manual or active alarm [16]. Cao et

Table 3. Two detection methods for the diagnosis of SMI (n, %)

Group	Positive	Negative
Remote ECG monitoring system (n=26)	23 (88.46)	3 (11.54)
Artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system (n=26)	24 (92.31)	2 (7.69)
χ^2	0.221	
P	0.638	

Note: SMI: symptomatic myocardial ischemia.

Table 4. Two detection methods for the diagnosis of AMI (n, %)

Group	Positive	Negative
Remote ECG monitoring system (n=94)	81 (86.17)	13 (13.83)
Artificial intelligence-enabled ECG algorithm combined with remote ECG monitoring system (n=94)	92 (97.87)	2 (2.13)
χ^2	8.766	
P	0.003	

Note: AMI: asymptomatic myocardial ischemia.

al. confirmed that remote cardiac detection was not limited by time and region, and had the characteristics of fast transmission, high fidelity, and good clinical promotion and application [17]. Artificial intelligent-enabled ECG algorithm can accurately detect each abnormal heartbeat in MI patient and give real-time alarm [18]. However, some patients have no significant symptoms, which may be related to the decreased degree and time of MI in patients and the failure to reach the pain threshold. Remote cardiac detection can continuously monitor patients with resting MI and those without significant symptoms, achieving continuity and remote detection [19]. Artificial intelligence-enabled ECG algorithm can significantly improve the service efficiency of remote cardiac monitoring of MI and increase the monitoring sensitivity and real-time performance [20]. Vylala et al. proposed that through intelligent wearable devices combined with artificial intelligence, intelligent heart remote monitoring terminal and remote big data platform could be realized, which can collect patients' ECG signals for real-time transmission and analysis of early warning, thereby improving the diagnostic accuracy of MI [21]. This study found that the positive detection rate of cardiac remote monitoring based on artificial intelligence-enabled ECG algorithm was higher than that of cardiac remote monitoring in MI patients. It indicated that cardiac remote monitoring based on artificial intelligence-enabled ECG algorithm could improve the detection rate of MI patients.

Studies have shown that the risk of ST segment depression in MI patients increases by 1.819 times for each increase in the number of coronary vessel lesions, and the probability of ST segment depression in patients with coronary artery stenosis >75% is 88% [22]. Liu et al. showed that hypoxia and ischemia of cardiomyocytes in patients with coronary artery lesions of different degrees would damage cardiomyocyte metabolism, make ventricular recovery very slow, and induce cardiac adverse events [23]. Zhou et al. indicated that the assessment of the number of coronary artery lesions and the degree of stenosis in MI patients is conducive to the clinical diagnosis and treatment of MI [24]. Therefore, improving the detection rate of coronary artery lesions and stenosis in MI patients plays a crucial role in the diagnosis of MI. Remote cardiac monitoring is developed based on dynamic ECG, which can detect ST segment changes in MI patients and indicate the presence of coronary vascular lesions and stenosis according to the degree of ST segment changes [25]. In this study, a further comparative study was conducted on SMI and AMI patients, and the ST segment changes in SMI patients were more pronounced with a reminder of severer condition, which finding was consistent with the results of previous studies [26]. Previous studies on AMI have shown that the onset time of AMI patients has circadian rhythm, which is basically consistent with the occurrence regularity of myocardial infarction patients [27]. This study also revealed that both SMI and AMI patients had circadian rhythm, with the lowest frequency of attack from 0:00 to 06:00 and the highest frequency from 06:01 to 12:00, consistent with the results of above studies.

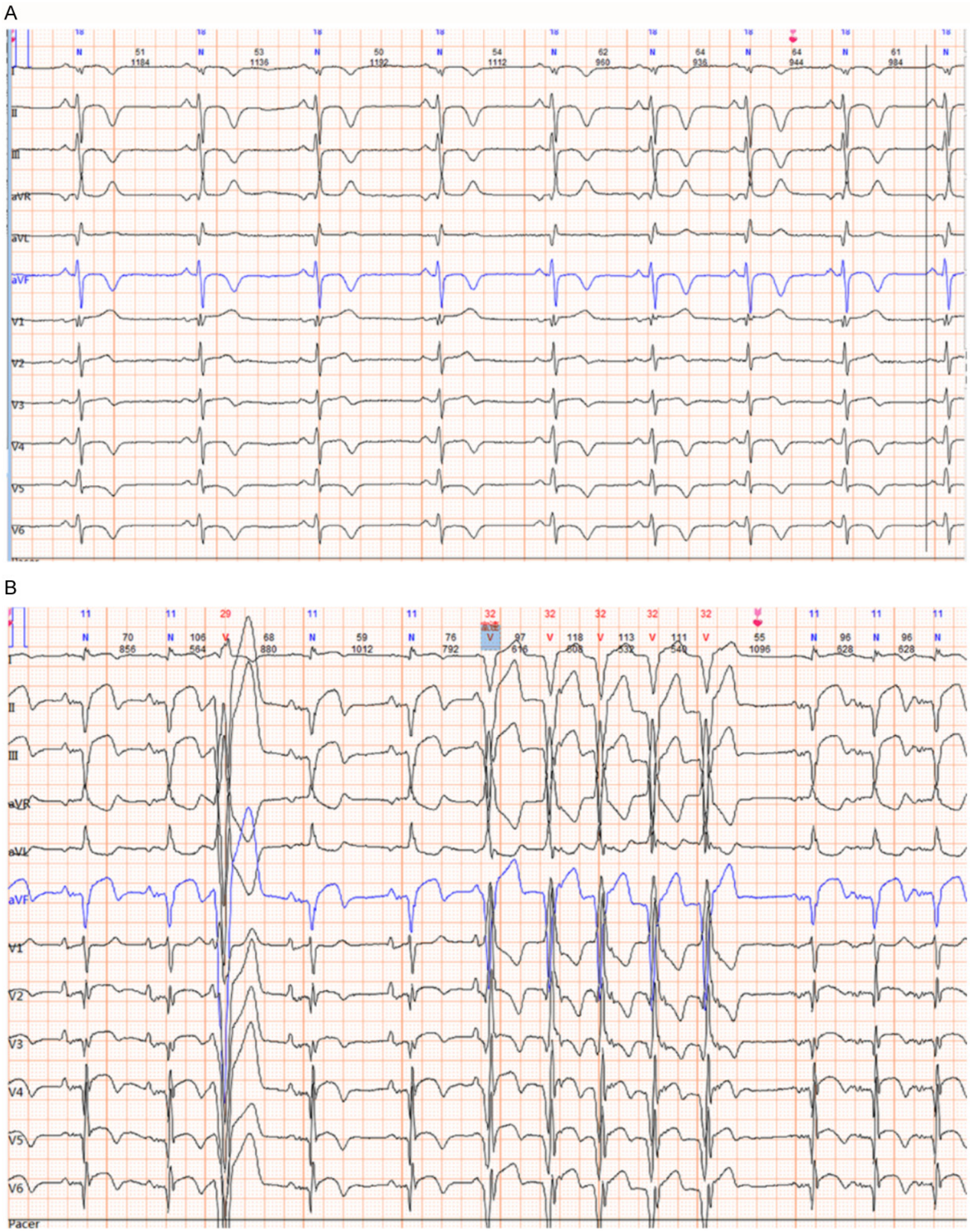

Figure 2. ECG of MI. A: The EEG of asymptomatic patients with MI; B: The EEG of symptomatic patients with MI. MI: myocardial ischemia.

This study also has shortcomings with single research content and a few research time points, which may affect the results. Therefore, time points, experimental data and samples should be expanded in future studies to provide a strong clinical basis for the diagnosis of AMI.

In conclusion, CRMS based on artificial intelligence-enabled ECG algorithm mode can signifi-

Table 5. Comparison of general information in SMI and AMI patients ($\overline{x}$±sd)

Item	SMI (n=26)	AMI (n=94)	χ^2/t	P
Average age (years)	51.9±9.1	51.2±9.6	0.740	0.332
Gender (male/female)	18/8	66/28	0.009	0.923
BMI (kg/m^2)	25.43±2.41	25.03±2.16	0.417	0.815
Combined disease (n)				
Hypertension	15	50	0.166	0.684
Hyperlipemia	6	15	0.715	0.398
Type 2 diabetes	13	57	0.948	0.330
Smoking	22	74	0.442	0.506
Number of stenosed coronary vessel (n)			1.856	0.395
Single vessel	6	13		
Double vessel	9	34		
Triple vessel	11	53		
Degree of coronary artery stenosis (n)			1.763	0.414
Mild stenosis (<50%)	4	10		
Mitral stenosis (50%~75%)	10	27		
Severe stenosis (>75%)	12	57		

Note: SMI: symptomatic myocardial ischemia; AMI: asymptomatic myocardial ischemia.

Table 6. Comparison of attacks in SMI and AMI patients ($\overline{x}$±sd)

Item	SMI (n=26)	AMI (n=94)	t	P
Degree of ST segment decline (mV)	0.23±0.07	0.15±0.06	5.799	<0.001
Duration of ST segment decline (min)	2.24±1.03	0.85±0.58	10.781	<0.001
Threshold variability of MI (%)	22.65±3.03	15.92±2.89	10.411	<0.001

Note: SMI: symptomatic myocardial ischemia; AMI: asymptomatic myocardial ischemia.

Table 7. Comparison of onset time in SMI and AMI patients (n, %)

Time period	SMI (n=80)	AMI (n=398)	χ^2	P
0:00-06:00	5 (6.25)	33 (8.29)	0.337	0.953
06:01-12:00	46 (57.50)*	211 (53.02)*		
12:01-18:00	14 (17.50)*,#	73 (18.34)*,#		
18:01-24:00	15 (18.75)*,#	81 (20.35)*,#		

Note: Compared with 0:00-06:00, *P<0.05; compared with 06:01-12:00, #P<0.05. SMI: symptomatic myocardial ischemia; AMI: asymptomatic myocardial ischemia.

cantly improve the detection rate of AMI. In addition, the ST segment changes of AMI patients are small, and the onset presents a certain circadian rhythm.

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Disclosure of conflict of interest

None.

Address correspondence to: Nengbin Dong, Functional Examination Center, The First People's Hospital of Chenzhou City, No. 102 Luojiajing, Beihu District, Chenzhou 423000, Hu'nan Province, China. Tel: +86-13607351880; E-mail: dnb1880@126.com

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