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Improving staff response to seizures on the epilepsy monitoring unit with online EEG seizure detection algorithms

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ABSTRACT

Objective: User safety and the quality of diagnostics on the epilepsy monitoring unit (EMU) depend on reaction to seizures. Online seizure detection might improve this. While good sensitivity and specificity is reported, the added value above staff response is unclear. We ascertained the added value of two electroencephalograph (EEG) seizure detection algorithms in terms of additional detected seizures or faster detection time.
Methods: EEG-video seizure recordings of people admitted to an EMU over one year were included, with a maximum of two seizures per subject. All recordings were retrospectively analyzed using Encevis EpiScan and BESA Epilepsy. Detection sensitivity and latency of the algorithms were compared to staff responses. False positive rates were estimated on 30 uninterrupted recordings (roughly 24 h per subject) of consecutive subjects admitted to the EMU.
Results: EEG-video recordings used included 188 seizures. The response rate of staff was 67%, of Encevis 67%, and of BESA Epilepsy 65%. Of the 62 seizures missed by staff, 66% were recognized by Encevis and 39% by BESA Epilepsy. The median latency was 31 s (staff), 10 s (Encevis), and 14 s (BESA Epilepsy). After correcting for walking time from the observation room to the subject, both algorithms detected faster than staff in 65% of detected seizures. The full recordings included 617 h of EEG. Encevis had a median false positive rate of 4.9 per 24 h and BESA Epilepsy of 2.1 per 24 h.
Conclusions: EEG-video seizure detection algorithms may improve reaction to seizures by improving the total number of seizures detected and the speed of detection. The false positive rate is feasible for use in a clinical situation. Implementation of these algorithms might result in faster diagnostic testing and better observation during seizures.

1. Introduction

Video-EEG monitoring in an epilepsy monitoring unit (EMU) is widely used as a diagnostic tool in people suspected of having a seizure disorder. It can be used to determine seizure type and classification, to distinguish epilepsy from nonepileptic seizures, or to examine or evaluate therapeutic options [1,2]. People are continuously monitored by staff in a separate observation room, using real-time video, audio, and EEG recordings. When seizures are detected, nursing staff enter the subject's room to reduce the risk of adverse events such as falls, respiratory compromise, and injuries [3]. Standardized tests are also performed to assess consciousness and cognition during seizures, which helps to determine seizure semiology and type [4,5].

Staff supervision demands skills and uninterrupted attentive observation for any sign of a seizure, as otherwise, they may be missed. One study showed a response rate of 41% to seizures with a mean latency over 2 min [6]. While response rate and time may vary between EMUs, response rates are limited by human abilities. Seizures are often recognized by clinical manifestations, so seizures showing subtle, clinical semiology or none are more often missed.

Online seizure detection algorithms might help detecting seizures that could have otherwise been missed or recognized too late. Seizures can be detected with a variety of signals, such as movement, electrodermal activity, heart rate, and EEG. We focused on EEG seizure detection as it is closest to the source of epilepsy, specific to epilepsy, and measured as standard on every EMU. EEG seizure detection has been ascertained since 1982, and much research has since been performed on various approaches to seizure detection [7–10].

Recently, EEG seizure detection software, such as Encevis EpiScan and BESA Epilepsy, has become commercially available. Encevis EpiScan uses two modules, which detect epileptiform activity [11,12]. To detect seizures, the extracted features are continuously compared with past information from the EEG. The BESA Epilepsy software estimates normalized energy and integrated power for different frequency bands [13,14].

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This algorithm is based on the hypothesis that seizure activity manifests itself by a change in frequency and amplitude that is distinct from nonseizure or background activity. When extracted features are above a threshold for longer than 10 s, a seizure is detected. The algorithm has been developed and tested for adults.

EEG detection algorithms have been studied thoroughly and show good sensitivity and low false response rates in detecting epileptic seizures [8,9]. For Encevis EpiScan a sensitivity of 81% with a false-detection rate of 0.30 per hour has been reported [15]; BESA Epilepsy was reported to have sensitivity of 87% with a false-detection rate of 0.22 per hour [14]. It is, however, unclear what added value the seizure detection algorithms provide to EMU seizure monitoring, as these algorithms are not widely implemented [16]. It is important to know the added value, as seizure detection systems are not standalone but aids for staff already present. We investigate this added value by assessing the following: 1) the current response rate and latency of staff to seizures; 2) the sensitivity, latency, and false positive rates of Encevis EpiScan and BESA Epilepsy; 3) the value added to the current response in terms of additional detected seizures and shorter latency; and 4) which monitoring could benefit from these algorithms.

2. Methods

2.1. EMU setting

The added value of a detection algorithm depends on the work setting and the staffing; to allow comparisons, we describe here our setting: It is an 8-bed unit, where each individual stays in a separate room, for up to 5 days. Three to four remote control cameras are installed in each room to capture the whole room. Individuals have call buttons to alert staff.

Subjects are monitored continuously by staff (specialized nurses) in an observation room, where a real-time EEG, electrocardiogram (ECG), video, and audio stream is shown for each room. An intercom system can be used for communication. When a seizure is noticed, the subject is attended to ensure safety and execute standardized diagnostic tests. Three nurses are present during the daytime and two during the night. No automated seizure detection techniques are used.

2.2. EEG recordings

A Micromed EEG system (Micromed, Mogliano Veneto, Italy) was used to record EEGs with a sampling frequency of 256 Hz, in a frequency band of 0.01 to 1000 Hz. The international 10–20 electrode placement system was used. Some individuals had additional electrodes to provide higher spatial sampling. After recording and reporting, it is standard practice to cut EEG and video files to decrease storage space. Only diagnostically relevant parts of the registration, for example diagnostic tests and seizures, are stored.

2.3. Data selection

Seizures between May 2014 and April 2015 were included retrospectively in a seizure database. Only seizures confirmed as epileptic in the corresponding EEG report and longer than 5 s were included. To prevent overrepresentation only two seizures per subject were included. If more than two seizures were present two of the first five were randomly selected. It's important to perform diagnostic tests in these initial seizures, so staff response is required; this might not be the case for later seizures. The seizure database encompasses a representative sample of all seizure types occurring in the EMU. Seizures where staff was already present at the start of the seizure were excluded, as response could not be evaluated. Seizures where the patient alerted the staff were not excluded. Call buttons will not be removed from clinics when using EEG-based seizure detection and is therefore an important addition to visual recognition of seizures by staff. The EEG file duration of the seizures could vary depending on how files were cut.

An additional database (the 24-hour database) consisted of nonstop EEG recordings without selection was created. These recordings represent the complete setting on an EMU and can therefore be used to calculate false positives. The 24-hour database included recordings of 30 consecutive recordings from September 2016. For every subject, 16 to 24 consecutive hours of the recording were randomly included.

This study was carried out in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans.

2.4. Scoring of the registrations

Seizures' start and end in both databases were identified by trained reviewers. Four different time points were scored: clinical seizure onset (CSO), clinical seizure end (CSE), electrographic seizure onset (ESO), and electrographic seizure end (ESE), as can be seen in Fig. 1. The ESO was defined as the moment where the first EEG seizure pattern could be seen and the ESE where it ends. The CSO was defined as the start of the first clinical symptom. The CSE was defined as the time when subjects were able to resume normal activities, as up to that point, it is of value to respond to seizures. The CSO–CSE period may therefore include postictal symptoms.

For the seizure database, the electrographic and clinical seizures characteristics were also scored to evaluate how easily changes could be detected by an observer. Both sets of characteristics were scored using values between 1 and 4, representing no visible manifestations (1) to very clear manifestations (4) from the perspective of the nurses who monitor the subjects. The characteristics were scored every 5 s until staff responded, up to the first 60 s of the seizure. From these scores, a mean value was calculated. Seizure classification was also collected from EEG reports.

The interictal EEG in the 24-hour database was evaluated to investigate whether epileptiform activity would influence the false positive rate. Four categories were used: 'Normal interictal EEG', 'Abnormal interictal EEG with nonspecific nonepileptiform abnormalities', 'EEG with some epileptiform abnormalities', and 'EEG with frequent epileptiform abnormalities', based on the EEG report.

Staff response was evaluated by retrospectively reviewing the videos from the seizure database. A response was defined as staff entering the room of the subject or using the intercom any time from the seizure onset until 10 s after the end of the seizure (when EEG and clinical manifestations have both stopped).

All recordings were retrospectively analyzed using Encevis EpiScan and BESA Epilepsy. The detection algorithms should operate the same in an online situation, but due to unavailability of online functioning this could not be tested.

2.5. Sensitivity

We calculated the detection sensitivity of staff, Encevis EpiScan, and BESA Epilepsy. A correct detection was defined as detection within the period from 10 s before the start of a seizure (CSO or ESO) to 10 s after the end of a seizure (ESE or CSE) (Fig. 1).

2.6. Latency

Latency of staff, Encevis EpiScan, and BESA Epilepsy were calculated from electrographic seizure onset (ESO). For BESA Epilepsy, 10 s were added to account for the delay in the algorithm's online functioning; the algorithm places detection markers at seizure onset after having registered 10 s of the seizure. Median latencies and p5–p95 percentile ranges of the latencies were calculated.

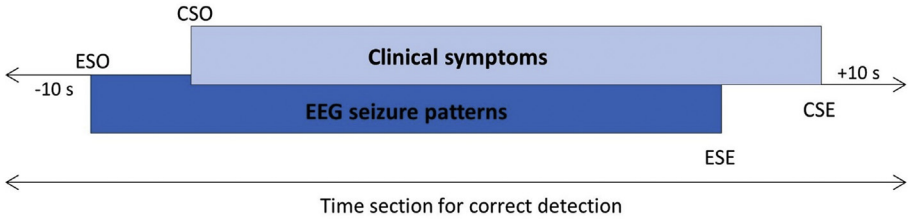

Fig. 1. Visualization of timing of a seizure, which might vary between subjects. CSO (clinical seizure onset), CSE (clinical seizure end), ESO (electrographic seizure onset), and ESE (electrographic end) were scored for every seizure. A correct detection was defined as detection within the 10 s before the start of the seizure until 10 s after the end of the seizure.

2.7. False positives

The false positive rate of Encevis EpiScan and BESA Epilepsy was calculated on the 24-hour database. A false positive is defined as a detection that does not take place during a seizure, i.e., beyond 10 s before the start of a seizure (CSO or ESO) and 10 s after the last end (ESE or CSE). When a false positive occurred, a black-out period of 10 s was defined, in which no new false positives could occur. The median false positive rate and percentile ranges p5–p95 were calculated.

2.8. Statistical analysis

The difference in sensitivity between seizure characteristics (adulthood, seizure classification, clinical characteristics, and electrographic characteristics) (separately for staff, Encevis EpiScan, and BESA Epilepsy) were tested for statistical significance with a Chi-square test. If a characteristic could not be determined, the recording would be removed from this analysis.

We also assessed the effect of subject age and the amount of interictal abnormalities in the EEG on the false positive rate with a Kruskal–Wallis test. The significance level was set at $p \leq 0.05$. All analyses were performed using MATLAB (R2017a, The MathWorks Inc.).

3. Results

In total, 188 seizures in 115 subjects were included in the seizure database and 617 h of 30 subjects in the 24-hour database. The mean age in the seizure database was 28.7 years (SD 17 years) and was 24.2 years (SD 15.5 years) in the 24-hour database. Included seizures were generalized onset seizures (9.6%), focal onset seizures with temporal lobe semiology (42.6%), focal onset seizures with extratemporal lobe semiology (45.7%), and seizures that could not be classified (2.1%).

3.1. Sensitivity

The sensitivity of staff, Encevis EpiScan, and BESA Epilepsy are shown in Table 1. Of 62 seizures missed by staff, 41 were recognized by Encevis EpiScan and 24 by BESA Epilepsy. Sixteen seizures were recognized only by staff. The comparison of sensitivity of Encevis EpiScan and BESA Epilepsy for all seizures and all seizures undetected by staff are shown in Fig. 2. The influence of different seizure characteristics on the sensitivity are shown in Table 2.

Table 1
Performance of staff, Encevis EpiScan, and BESA Epilepsy. Sensitivity, median latency of detection from the start in the EEG (ESO), and median false positives per 24 h is shown. For BESA Epilepsy, 10 s was added to account for the delay in the algorithm's online functioning.

	Staff	Encevis EpiScan	BESA Epilepsy
Sensitivity	67.0%	77.6%	65.4%
Median latency of detections in seconds (p5 to p95)	31 (−5 to 98)	10 (−4 to 50)	14 (6 to 68)
Median false positives per 24 h (p5 to p95)	–	4.9 (1.2 to 13.8)	2.1 (0 to 222.7)

3.2. Latency

Median latency with p5 and p95 are shown in Table 1. Fig. 3 shows the time of detection of Encevis EpiScan and BESA Epilepsy compared to staff latency. In 83.5% of the 103 seizures detected by staff and Encevis EpiScan, the algorithm detected the seizure faster than the staff response. In 81.6% of the 98 seizures detected by staff and BESA Epilepsy, the algorithm detected the seizure faster than the staff response. This would lead to a median improvement of 18.1 s for Encevis EpiScan and a median improvement of 15.6 s for BESA Epilepsy. When correcting for walking time of 10 s from the observation room to the subject, Encevis EpiScan was still faster in 65.0% of detected seizures and BESA Epilepsy in 65.3% of detected seizures.

3.3. False positives

The median false positive rates can be seen in Table 1, and a histogram of the false positive rates per subject is shown in Fig. 4. Encevis EpiScan had low false positive rates for almost every subject. BESA Epilepsy had zero false positives for most subjects but also some outliers with many false positives. Most false positives with Encevis EpiScan occurred during the first hours. This is probably due to a learning period, in which the algorithm needs to establish a baseline. If the alarm of Encevis EpiScan was turned off during the first hour, the false positive rate would decrease by 36.4% and by 46.1% if it were turned off for the first 2 h.

Children had a higher false positive rate than adults for Encevis EpiScan ($p = 0.0430$), with a median false positive rate of 6.99 per 24 h for children and 4.47 per 24 h for adults. The difference in false positive rate between the abnormalities in the interictal EEG was not statistically significant.

BESA Epilepsy also had a higher false positive rate in children than in adults ($p = 0.0057$), with a median false positive rate of 39.1 per 24 h for children and 1.28 per 24 h for adults. Additionally, EEGs with frequent epileptiform abnormalities had a significantly ($p = 0.0308$) higher false positive rate, with a median false positive rate of 33.1 per 24 h (compared to 1.16–9.86 for EEGs with fewer abnormalities).

4. Discussion

Reaction to seizures can be improved by online EEG seizure detection algorithms by improving the number of detected seizures and the response latency after start of a seizure. We were able to show that more than half of the undetected seizures could be recognized by EEG seizure detection algorithms. For most seizures the detections by both algorithms preceded detection by staff. The algorithms had acceptable median false positive rates.

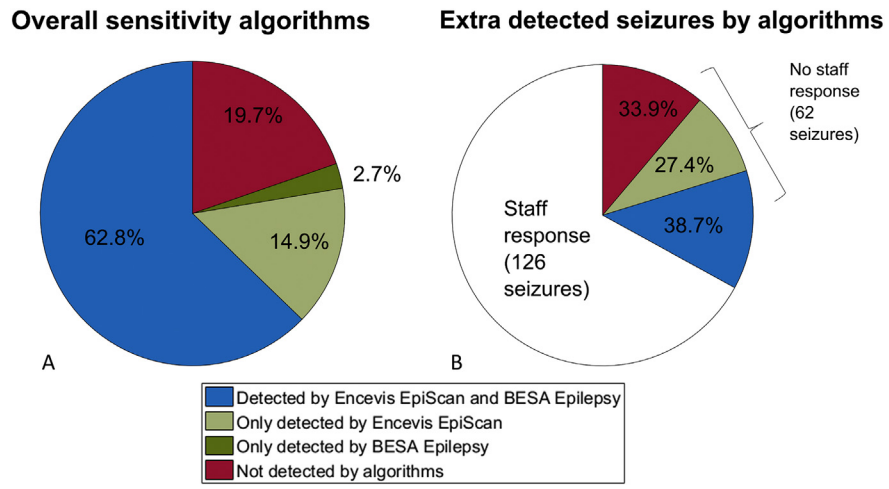

Fig. 2. Overall sensitivity of seizure detection algorithms Encevis EpiScan & BESA Epilepsy on all 188 seizures (A) and sensitivity for seizures missed by staff (B).

The staff response and latency that we found is better than previously described where a response rate of 41% with an average latency of 142.3 s has been shown [6]. This may be due to differences between EMU settings, e.g., staff experience or EMU layout. The sensitivity and specificity of the algorithms that we described are comparable with those from previous reports [14,15]. Latency has not been previously described. The added value above staff already present has not previously been reported. This information is key, since a seizure detection algorithm will not be a stand-alone system but an addition to current staff.

Staff response and sensitivity of detection algorithms are influenced by seizures and individual characteristics. When there is a low staff response rate but algorithms are able to detect seizures, people could particularly benefit from these algorithms. Staff response was highly dependent on clinical characteristics as response is based on symptoms seen on the video stream. Conversely, algorithms were mostly dependent on the presence of electrographic changes. This influence is also reflected in the sensitivity for different seizure classifications. For example, generalized seizures are electrographically and clinically very clear and therefore have a high response rate by staff and algorithms. Focal onset seizures with extra-temporal lobe semiology, on the other hand, were short with few clinical and electrographic changes and therefore have a lower response rate by staff and algorithms. Thus, people with less clear seizures showing electrographic changes could benefit from these algorithms. In particular, seizures with temporal lobe semiology had low staff sensitivity but a high sensitivity on the algorithms. Children might benefit from seizure detection algorithms, as staff sensitivity was lower in children. A higher false positive rate was, however, found for children. This might be due to variations in EEG patterns in children, making it more challenging to differentiate normal EEG from ictal patterns [17]. Children in our dataset more often had EEG abnormalities, which also influenced the specificity of the algorithms. Encevis EpiScan still had an acceptable false positive rate for children making it more appropriate than BESA Epilepsy for children, which had not previously been tested in children.

There are a number of limitations to our study. The algorithms could not be tested online, as at the time of the study they were not ready for online implementation. Therefore, the true effect of these algorithms could not be assessed. Two different databases were also used to test the sensitivity and false positive rates of the algorithms. Testing sensitivity and false positive rates in the same full recordings would provide a better validation of the algorithms, allowing estimation of the false positives relative to the true positives. Additionally, performance has been tested on preselected data files. A dataset of full recordings including all type of seizures was not available at the time of the study. This study did not include any nonepileptic events. These events cannot be detected by EEG-based algorithms. However, research has shown a higher response rate of staff to psychogenic nonepileptic seizures,

Table 2
Sensitivity of staff, Encevis EpiScan, and BESA Epilepsy for different characteristics of seizures. The difference in sensitivity for specific characteristics was tested for statistical difference per detection method with a Chi-square test. Values under the significance level ($p \leq 0.05$) are presented in bold. If a characteristic could not be determined, these would be removed before further analysis.

		Staff		Encevis EpiScan		BESA Epilepsy	
		Sensitivity	p-Value	Sensitivity	p-Value	Sensitivity	p-Value
All subjects		67.0%	–	77.6%	–	65.4%	–
Age	Children under 18 year (n = 54)	59.3%	**0.03**	79.6%	0.68	72.2%	0.21
	Adults (n = 134)	70.1%		76.9%		62.7%	
Seizure classification	Generalized onset (n = 18)	88.9%	**0.004**	100%	<**0.001**	100%	<**0.001**
	Focal onset seizures Temporal (n = 80)	75.0%		86.3%		71.3%	
	Extratemporal (n = 86)	55.8%		64.0%		53.5%	
	Unclear classification (n = 4)	–		–		–	
Clinical characteristics	No visible changes (n = 27)	37.0%	<**0.001**	85.2%	0.51	66.7%	0.31
	Subtle clinical symptoms (n = 119)	67.2%		77.3%		61.3%	
	Clear clinical symptoms (n = 34)	82.4%		70.6%		73.5%	
	Very clear clinical symptoms (n = 8)	100%		87.5%		87.5%	
Electrographic characteristics	No visible changes (n = 6)	66.7%	**0.03**	66.7%	<**0.001**	0%	<**0.001**
	Subtle changes (n = 73)	54.8%		58.9%		39.7%	
	Clear focal changes (n = 73)	72.6%		89.0%		83.6%	
	Clear diffuse changes (n = 36)	80.6%		94.4%		91.7%	

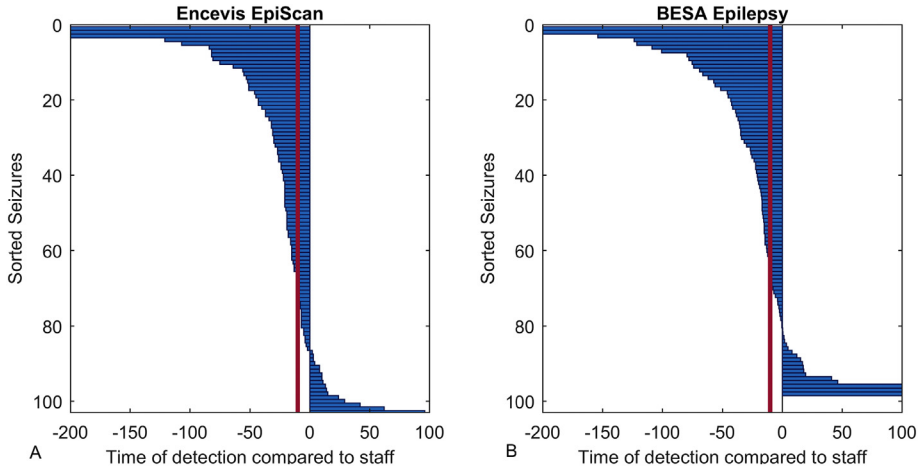

Fig. 3. Time of detection of the algorithms is shown compared to staff latency (0 s) for the seizures that were detected by the algorithm and staff. For BESA Epilepsy, 10 s was added to account for the delay in the algorithm's online functioning. An extra red line is drawn to take walking time of staff into account (10 s). Some outliers could not be shown in the figure; for Encevis EpiScan this was −1579, −611 and − 215 s and for BESA Epilepsy this was −552, −253, 309, 392 and 3173 s. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

compared to epileptic seizures [18]. Lastly, staff response can vary between different EMU settings. Depending on how staff are trained and subjects are monitored, the response rate may differ. Since lower response rates were found in another center, the added value in other centers might be higher than we described [6].

Future research should focus on testing these algorithms online on continuous unselected data. Additionally, performance of EEG seizure detection algorithms might increase when using multisensor seizure detection. We do not see substantial benefit from adding movement-based sensors or electromyographic sensors. These detectors perform best on tonic–clonic seizures or hypermotor seizures, which are already recognized by staff and algorithms. There might be an improvement when adding ECG seizure detection. Heart rate changes occur in all type of seizures and mostly in the beginning or even before electrographic start of a seizure [19,20]. Adding this type of seizure might increase sensitivity and latency, but more research on this topic is necessary.

5. Conclusions

Online EEG seizure detection algorithms can improve the staff response to seizures by detecting additional seizures and improving latency. The false positive rate is reasonable for use in a clinical setting. Implementation of these algorithms may help to ensure patient safety and improve the quality of diagnostics by assessing consciousness and cognition in a timely manner.

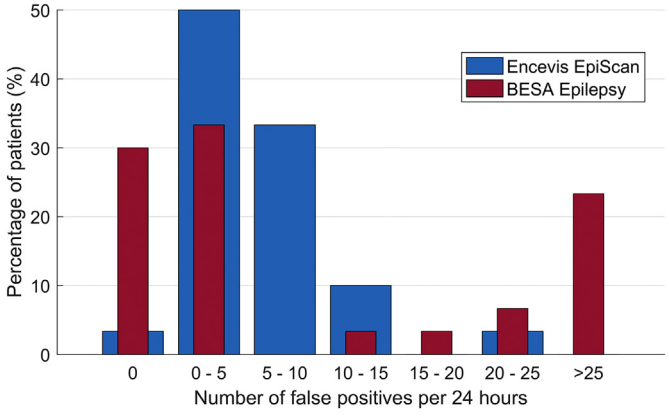

Fig. 4. Distribution of quantity of false positives for all subjects. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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Disclosure of conflicts of interest

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