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Alternative Input for Perfusion Management Devices: Voice Recognition for Data Input and the Effects on Charting and Perioperative Calculation Use

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Abstract: Technology in healthcare has become increasingly prevalent and user friendly. In the last decade, advances in hands-free methods of data input have become more viable in a variety of medical professions. The aim of this study was to assess the advantages or disadvantages of hands-free charting through a voice-to-text app designed for perfusionists. Twelve clinical perfusion students using two different simulated bypass cases were recorded and assessed for the number of events noticed and charted, as well as the speed at which they accomplished these steps. Paper charts were compared with a custom app with voice-to-text charting capability. Data was analyzed using linear mixed models to detect differences in length of time until a chartable event was noticed, and how long after noticing an event it took to record the event. Timeliness of recording an event was made by assessing log-transformed time data. There was significantly more information recorded when charting on paper, while charting with voice-to-text resulted in significantly faster mean time from noticing an event to the recording of it. There was no significant difference between how many events were noticed and recorded. When using paper charting, a higher percentage of events that were missed were drug administration events, while voice charting had a higher percentage of missed events that were associated with cardioplegia delivery or bypass timing. With a decreased time interval between noticing an event and charting the event, speech-to-text for perfusion could be of benefit in situations where many events occur at once, such as emergency situations or highly active portions of bypass such as initiation and termination. While efforts were made to make the app as intuitive as possible, there is room for improvement. **Keywords:** perfusion, charting, voice-input, paper charting, operating room efficiency, simulation. *J Extra Corpor Technol. 2021;53:286–92*

In 2009, the American Recovery and Reinvestment Act mandated that by 2014, all public and private healthcare providers would need to adopt some form of electronic medical record (EMR) and demonstrate meaningful use of it (1–3). Financial incentives were included in this, and hospitals nationwide who had not already embraced the advancement of the digital age began to buy into the associated Electronic Health Record Incentive Programs. The focus of these programs was to ensure electronic capture of clinical data and to provide patients with copies of that data (1). After that step was implemented, a process of continuous quality improvement could be used to ensure an advancement of patient care.

While individual departments were not mandated by law to convert to EMRs, technology provides many benefits. They tend to reduce medical error, help make prescriptions more reliable, and streamline billing, all while improving productivity and workflow of the associated healthcare workers (1). Some departments within the hospital, such as operating rooms (ORs) and intensive care units, tend to be more technologically advanced environments, in part because the patients and employees stand to gain more from small increases in workplace efficiency (4). While there is somewhat inconsistent data supporting that EMR implementation frees up time for clinicians to use elsewhere, one undeniable benefit is the increased amount and accuracy of data collected (5,6). Major limiting factors for effective departmental conversion to an

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EMR seem to be the cost, the initial learning curve, and the extent to which the system in question allows for fast, intuitive input of data (3–8).

OR procedures are typically more time dependent and critical in nature, and real-time charting during stressful events is not easy (9). Most data that is not automatically gathered is recorded after the event and this can lead to misinformation or lack of information (9). New advances in technology that promise to reduce this error has the potential to be extremely helpful in a variety of situations. These new options are often variations on hands-free methods of data input, such as voice activated, gesture controlled, or eye tracking software (10). Of those, voice recognition and speech-to-text are some of the most extensively tested and applied hands-free technologies that are widely available (10). This explains why they are more likely to be used across a growing variety of platforms, including EMRs.

As with all new technologies, these new systems require testing, validation, and proof of function before they become widely applied. This process is why much of this technology has been slow to advance through the healthcare field (4,10). However, the benefits of continuous data collection that is offered by EMRs can not only lead to better identification and reaction to patient parameters outside of acceptable limits, but also better postoperative review, analysis, and growth from events that makes it an attractive option for administrators (11). AmSECT's guidelines and many hospital policies include sections regarding continuous quality improvement (12). This may include postoperative review of the "big data" of a perfusion department to help inform perfusionists of areas for improvement, reinforce compliance with standards, allow opportunities to engage in the direction of improvement initiatives, and enhance research opportunities (13). Therefore, hands-free methods of charting that allow for faster, and more timely input of data by the perfusionist have the potential to be quite beneficial in advancing the profession, and should be evaluated for possible future applications.

MATERIALS AND METHODS

Local Institutional Review Board approval for exemption status was obtained and consent of all participants was obtained prior to beginning simulations. Twelve perfusion students from the University of Nebraska Medical Center's Clinical Perfusion Education Program volunteered to participate in the study, each completing two different simulated bypass cases, one with a paper chart and one with the custom voice-to-text charting method with a working name of PerfNote. Each charting method came with an instruction sheet to indicate what the charting expectations were, and any limitations associated with the method. Each scenario had equally formatted patient information sheets to allow for comparable baseline data. Students were randomized as to which simulated case and which charting method they received first, and differences between those categories and the fact that each student contributed data twice were adjusted for using linear mixed model analysis. Students were recorded by video to allow for stop-motion analysis of timing for the two charting methods. The intervals between the occurrence of an event, the recognizing of that event, and the recording of the event were measured.

The simulations were simple bypass cases programmed by the authors and run on a Califia 3.0 simulator (Biomed Simulation Inc., San Diego, CA). Each simulation had 16 events with fixed timing that could be compared. These events included recording timing of bypass and cross-clamp, charting patient data, drug administration, activated clotting time, and cardioplegia administration. Events that were not noticed or were noticed but not recorded were counted as missed events. To compare the timeliness of recording events, lognormal distribution was assumed. PerfNote was coded by the authors using Android Studio 3.5.2 (JetBrains s.r.o., Prague, Czech Republic) and loaded on a Kindle Fire HD 8 (Amazon.com, Seattle, WA). The paper chart was copied from the standard pump record used at our institution, last revised in July 2006, and of which the participants had some familiarity. All statistical analysis was performed using SAS software version 9.4 (SAS Institute Inc., Cary, NC).

RESULTS

Primary outcome parameters fell within two categories: recorded data and timeliness data. Recorded data considers whether any particular event was noticed, and or recorded, while timeliness data considers the time intervals between those events. Overall, no significant difference was found between the mean proportion of events noticed between the charting mechanisms (p = .12), as shown in Figure 1, wherein the proportion of events noticed when charting on paper was .94, and the proportion when charting by voice was .92.

Most events were noticed and recorded immediately by the participants, so data was broken down into three categories: events that were noticed immediately, noticed with a delay longer than 5 seconds, or not noticed at all (Table 1, Figure 2). There was no statistical difference in the numbers of events in each of those categories.

To determine whether there was a difference in the amount of data that was recorded overall, the percentage of recorded events was compared between the two

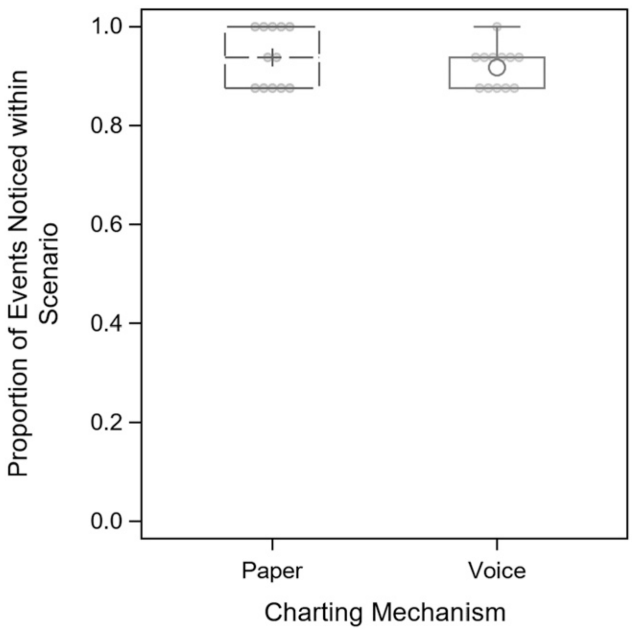

Figure 1. There was no significant difference in the model adjusted mean proportion of events noticed between the paper charting mechanism (mean = .94 events, SE = .01) and the voice charting mechanism (mean = .92 events, SE = .01), $p = .12$.

groups. When looking at all of the events, participants were significantly more likely to record events when using paper charting (Figure 3). This was true even when adjusting the data set to exclude events that were never noticed by the participant, and therefore could not have been recorded (Figure 4).

Timeliness analysis was run on log-transformed time interval data. Since the events that were charted immediately would not have any variation, and events that were not recorded did not have any data to analyze, timeliness data was analyzed only on events with delayed notice or delayed recording. Essentially, when there was a delay in event recording, was that delay longer based on the type of charging mechanism? From the data (Table 2), timeliness of noticing events was not significantly different between charting mechanisms; however, timeliness of recording events was significantly faster in the voice-charting group (Table 3).

While there was no statistical difference in the number of events that were not noticed, there was a larger number of total events that were not recorded when using voice charting rather than paper charting. Further analysis shows that individuals charting with paper were more likely to not record drug administration events, while individuals charting by voice were more likely to miss bypass events and cardioplegia delivery-related events (Figure 5).

While only 16 events were common points for comparison across all participants, additional charting was left up to the individual's discretion. The number of lines of patient data that were charted varied greatly. Paper charting averaged 7.25 lines of data per simulation (min: 3, max: 11, SD: 3.67) while voice charting averaged 4.75 lines per simulation (min: 2, max: 8, SD: 1.86). And while a baseline evaluation of patient data is common prior to going on bypass, variation in the prevalence of a complete baseline also existed between the two charting methods (Figure 6), with more students forgetting to chart a baseline entirely while using paper charting. This may be partially attributed to some students using the act of charting baseline data as a way to acclimate to the voice-based charting system.

DISCUSSION

One of the primary goals of the voice-to-text charting was to allow as much natural speaking as possible. Previous research on the topic of transitioning to electronic charting has noted that there is a significant learning curve associated with new technology, which can affect data collected during that transitional period (1,7,9,14). An app that could parse data from normal speech would potentially eliminate this issue (9). Alapetite studied the use of voice charting for anesthesiologists in 2008, but was limited by the technology of the time, and the program

Table 1. Table of notice by category.

	Charting Mechanism Event Totals			Model Adjusted Mean Proportion of Events		
	Paper	Voice	Total	Paper	Voice	Model p-Value
Notice immediate	119 61.98%	123 64.06%	242	.62 (.02)	.64 (.02)	.40
Notice delayed	61 31.77%	53 27.60%	114	.32 (.02)	.28 (.02)	.22
Unnoticed	12 6.25%	16 8.33%	28	.06 (.01)	08 (.01)	.12
Unrecorded	28	46				

Total data distribution for observations of events. Since most events that were noticed were noticed immediately, that data was summarized in categories: not noticed, immediately noticed, or delayed notice. There was no significant difference between the voice and paper groups in model adjusted mean proportion of events not noticed ($p = .12$), noticed immediately ($p = .40$), or noticed with a delay ($p = .22$).

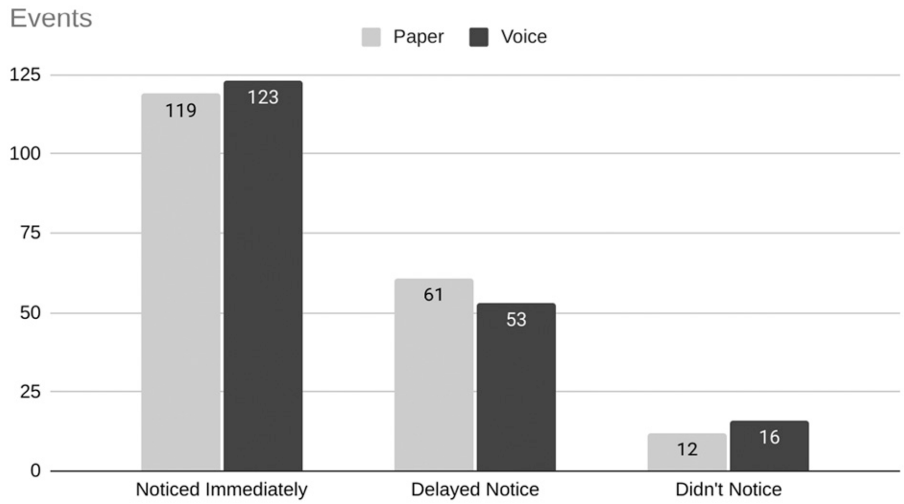

Figure 2. Distribution of events by immediacy of notice.

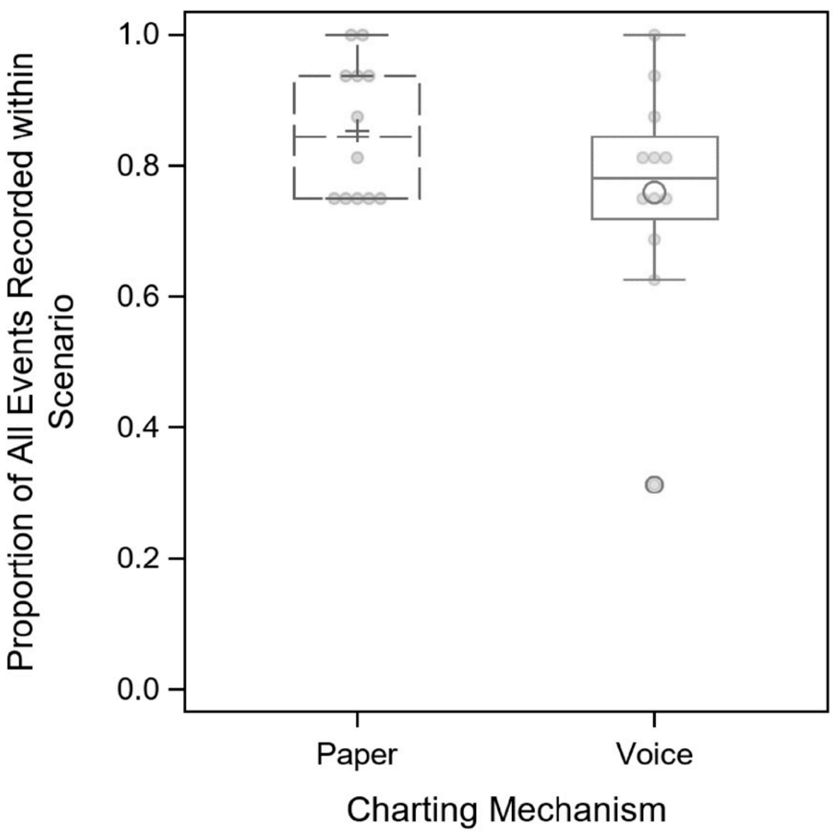

Figure 3. Students in the paper group had a significantly higher model adjusted mean proportion of events recorded (out of all events; mean = .85, SE = .03) compared to students in the voice group (mean = .76, SE = .03), p = .02.

that was used required stringent phrases to properly chart. To get around this, the subjects of that research used video and a "wizard of oz" charting method, wherein anything that was spoken that would have worked if the program was better, was counted as a successful charting event. While every effort was made to avoid the need for a similar effect in this study, it was not entirely successful and video data was used to supplement the charts where the voice-to-text failed. The primary source of this failure was not in parsing data from naturally spoken sentences, but in the voice-to-text function's database being unfamiliar with medical and OR specific jargon.

There were several other potential sources of differences between charting methods. Although the app produced

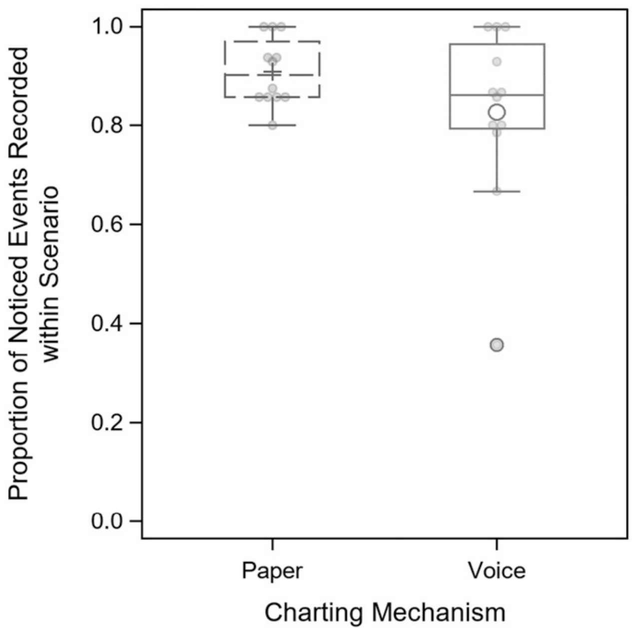

Figure 4. Students in the paper group had a significantly higher model adjusted mean proportion of events recorded (out of noticed events; mean = .91, SE = .03) compared to students in the voice group (mean = .83, SE = .03), p = .04.

timestamped data for a chart, it did not display the time of the last recorded data for the participant. It also did not have a visible list of parameters equal to those on the paper chart on the main screen, as a reference for charting, though it was available on the instruction sheet. Of greatest consternation to the participants, the audio recording had a fixed time interval after which it would stop, which most participants found to be far too short for convenient charting. Video analysis was made more critical because of this. The ability to pause, replay, and accurately pinpoint when the participant actually charted an event was only successful with the use of video analysis.

While video recording participants during their simulation was necessary for complete analysis of the time intervals, it is not without drawbacks. It is limited in the size and angle of the visual field, and similar to any research done with direct observation, it is subject to any observer bias that might occur. This potential for bias already existed; however, as participants knew ahead of time that they were being observed for their charting methods, as they were to participate in two simulated cases using different charting methods. While the possibility also existed to use the videos for stop-motion analysis of the time it took to complete charting events, this was not analyzed due to the inability of the programmer to change the time interval that the voice-input system was active for, resulting in some participants rushing through their charts, while others opted to use multiple shorter individual voice-input actions, and extend the time in that manner.

In Alapetite's study, part of the benefit of using video to analyze simulated cases was the ability to assess the mental workload of individuals. Mental workload was assessed by queueing theory, which measures the number of things that a person must remember to do at any given time. In our case, the mental queue would be the number of things that have yet to be recorded at any given time, and presumably this queue would grow as charting is put off in favor of taking action at the pump, and then shrink again when the simulation is less busy and the perfusionist has time to record data. High mental workload is associated with higher mental queues, and could result in events being forgotten, mis-remembered or errors occurring. However, upon analysis, there appeared not to be enough overlapping items within the simulation to test the relevance of queuing theory. However, mental workload may be presumed instead by the increased delay between time of event notice and time of event recording on events with

Table 2. Log transformed times from event-occurrence to event-notice for delayed-recording events.

	Paper Model Estimate Mean	Voice Model Estimate Mean	Model p-Value
Mean	13.51 seconds	10.63 seconds	.40
Mean of log transformed	1.78 log-seconds	1.68 log-seconds	.57
Geometric mean	5.94 seconds	5.37 seconds	(Same as mean of log transformed)

Table 3. Log-transformed times from event-notice to event-recording for delayed-recording events.

	Paper Model Estimate Mean	Voice Model Estimate Mean	Model p-Value
Mean	115.3 seconds	52.0 seconds	.04
Mean of log transformed	3.5 log-seconds	2.8 log-seconds	.0002
Geometric mean	34.4 seconds	16.7 seconds	(Same as mean of log transformed)

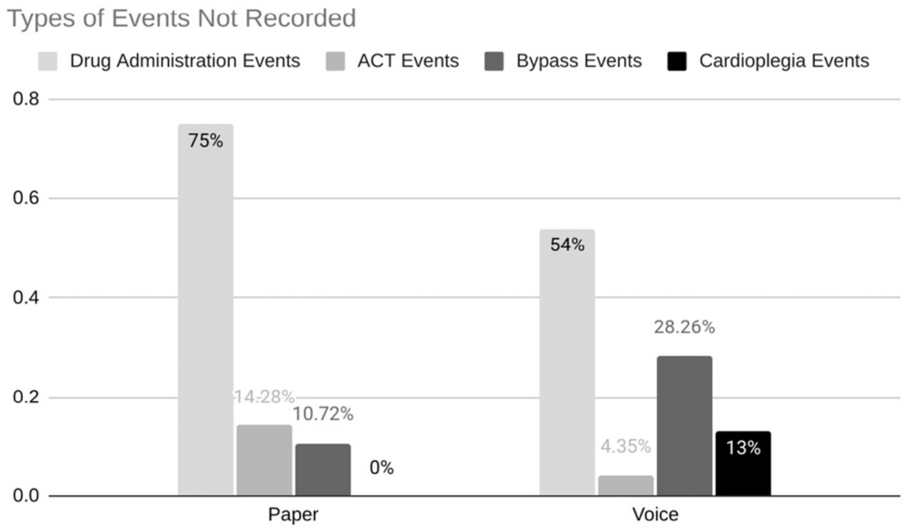

Figure 5. Types of events that were not recorded.

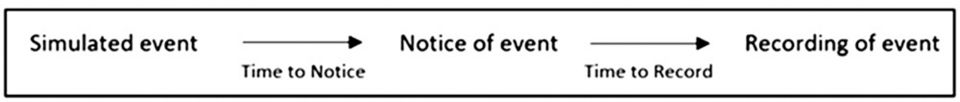

Figure 6. Flow of event timing.

delayed noticing. Voice-input charting was associated with significantly lower time between noticing and recording an event, which supports this idea; however overall, it was also associated with fewer events being noticed and being recorded, which may disprove the theory.

No participants used any additional functions that Perf-Note was able to offer, such as verbal playback of previously entered data, deletion of previous data, or verbal command of calculations such as oxygen delivery or oxygen consumption. This may also be a result of lack of familiarity with using similar functions in clinical scenarios previously, or the learning curve associated with an unfamiliar system. Though this lack of use did not allow for analysis of how intraoperative calculation use may vary with verbal access to results, the variation on how Perf-Note was used compared to how it was designed opens more opportunities to see how apps might be used most efficiently. While engaging in the simulations, several different methods were used by participants to use the app. Some recorded data concurrently with closed loop communication, eliminating all extra spoken words save for entry of lab results. Some participants left the Kindle in a single location and spoke to it from anywhere around the pump, while some physically returned to the Kindle every time they wanted to chart a line. Some individuals spoke more casually than others, or in shorter or longer bursts. Any further development on voice-to-text services for perfusion would do well to take all of these potential differences into account or factor them into features.

CONCLUSION

Perfusion, as with many professions, has needed to adapt as technology has become more pervasive (11) and health-care electronic data collection has become more widespread (2). The practice of adopting a new technology is often limited by available research of the practical benefits it can provide, the training time it requires, and its ease of use. In this research, naturally spoken phrases were used to test a voice-to-text system of charting and resulted in a reduction in the time delay between noticing an event and charting that event, which would result in timelier reporting of events in a perfusion record, but charting via paper still resulted in more data collected.

This experiment had limitations in that the app used was not able to perform to the degree that was anticipated, necessitating data collection through video analysis. And while this may be mitigated through better hardware and software, training to use the application would be necessary. Limitations in the amount of data collected through voice-to-text could have been a result of either the limitations of the app or the use of first-year perfusion students as study participants, for whom the paper chart might have offered more guidance.

Voice-to-text charting may not always be the most convenient method to chart for perfusionists, especially if silence is necessary and when there is information to be documented that colleagues do not need to be immediately aware of. However, the use of voice-to-text is not simply for intraoperative use. Extracorporeal membrane oxygenation, preoperative use or high-stress environments may benefit from having the option available. Additionally, the option to use hands-free charting may pave the way for other innovative technologies to be explored. Mobile apps in healthcare are not generally built specifically to replace people, other devices, or larger programs (though there are some exceptions). Instead, they are built to support and compliment them as a point of care resource that will inform better diagnoses and reduce medical error (15). This occurs particularly where there are gaps in function between devices or programs, or where a larger medical device has not yet implemented newer technological functions. In this way, apps can be a driving force for technological change within healthcare, as their presence points out where other technologies are failing or where they could grow. As a comparatively low-effort investment, apps may serve as a more timely addition to paper charting, or as a bridge toward transitioning to electronic charting for hospitals that still rely primarily on paper perfusion records. This is consistent with the initiatives for continuous quality improvement that are outlined in both the EMR implementation programs and AmSECT's Guidelines for Perfusion (13). The use of perfusion specific apps within the OR would aide in reducing the discrepancies between different parts of the surgical record as well as collecting real-time and more accurate data. These improvements would lead to higher quality patient care as the healthcare system continues to grow and adapt within the changing technological landscape (16).

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