Thesis Project Portfolio

Development of a Novel Device for Continuous Monitoring of Blood Coagulation During Cardiopulmonary Bypass

(Technical Report)

Analysis of Human and Machine Derived Racial Bias in Healthcare

(STS Research Paper)

An Undergraduate Thesis

Presented to the Faculty of the School of Engineering and Applied Science
University of Virginia | Charlottesville, Virginia

In Fulfillment of the Requirements of the Degree
Bachelor of Science, School of Engineering

William Arpin
Spring, 2024
Department of Biomedical Engineering

Table of Contents

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On my honor, I have neither given nor received any unauthorized aid on this assignment as defined by the honor guidelines for thesis related assignments

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Development of a Novel Device for Continuous Monitoring of Blood Coagulation During Cardiopulmonary Bypass

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Abstract`

In our study, we aimed to develop a novel method for continuous and non-invasive monitoring of blood coagulation during open heart surgeries. The goal was to reduce the reliance on bolus heparin injections by providing real-time feedback on clotting status. Leveraging Doppler velocimetry, we created a mathematical model to visualize velocity profiles of blood flow through a model heart-lung machine—an essential component in cardiac surgery that redirects blood flow while allowing surgeons unobstructed access to the heart. Our proof-of-concept testing focused on demonstrating how velocity profiles become blunter as blood clots. We analyzed frequency shifts and phase shifts. The frequency shift—from 4.09 ± 0.62 MHz to 3.21 ± 0.11 MHz — supported Doppler principles, decreasing as blood moved away from the transducer. However, due to the wide bandwidth, the wall echo frequency was different from the expected 5 MHz of the transducer, and the shift was much larger than expected. It is believed that this issue stems from the large bandwidth of the pulser. Regarding phase shift, initial observations showed none. Yet, further investigation revealed that the discrepancy resulted from a low sampling rate. By comparing velocity profiles with simulated data at 40 times the sampling rate used in the experiment, we confirmed the presence of phase shifts. Our findings pave the way for integrating this innovative approach into routine cardiac surgery practice, enhancing patient safety and surgical outcomes.

Introduction

In the mid-20th century, cardiac surgery faced significant challenges due to the inability to temporarily bypass the heart and lungs during complex procedures. Enter the heart-lung machine (HLM)—a remarkable invention that transformed open-heart surgery. In the 1920s, Soviet scientist Sergei Brukhonenko conducted experiments using canines and developed the first working HLM. However, it was not until later that this technology would be applied to humans[1]. Dr. John Heysham Gibbon, an American physician, built an experimental HLM in 1937. His machine used two roller pumps and could replace the heart and lung function of a cat[2]. On May 6, 1953, John Gibbon achieved a historic milestone by performing the first successful open-heart procedure on a human using an HLM[1]. Now, each year, approximately 1 million surgeries worldwide utilize HLMs to support patients during open-heart procedures. These machines take over the critical functions of oxygenating and circulating blood outside the body. However, a significant challenge arises when blood is removed from the patient: it tends to clot. This clotting risk extends to the interior of the HLM itself. To mitigate this, anticoagulant medications like heparin are administered to prevent perioperative clotting complications.

Heparin was discovered in the early 20th century by a Canadian biochemist named Jay McLean and his collaborator, William Henry Howell. They isolated it from liver cells and found that it had potent anticoagulant properties. The name "heparin" is derived from the Greek word "hepar," which means liver, reflecting its initial source[3]. Heparin is a complex molecule composed of repeating disaccharide units with uronic acid and glucosamine components. The sulfation of these components is crucial to heparin's anticoagulant activity[4]. Heparin works by enhancing the activity of antithrombin III (ATIII), a natural anticoagulant protein in the blood. When heparin binds to ATIII, it undergoes a conformational change, which significantly accelerates the inhibition of clotting factors such as thrombin (factor IIa) and factor Xa. By inhibiting these factors, heparin prevents the formation of fibrin clots, which are essential for wound healing but can be problematic during surgery. There are many different clinical applications of heparin including cardiac surgery, deep vein thrombosis (DVT), pulmonary embolism (PE), acute coronary syndromes (ACS), and hemodialysis.
During cardiac surgery, unfractionated heparin (UFH) is commonly administered with a cardiopulmonary bypass to prevent blood clotting. UFH exerts its anticoagulant effects primarily by antithrombin-mediated inactivation of factors IIa and Xa. UFH has a rapid onset of action, making it suitable for immediate use during surgery. It can also be reversed quicky if needed by administering protamine sulfate, which binds to UFH and neutralizes its effects. The dosing of UFH is adjusted based on the patient's weight, target activated clotting time (ACT) – the time it takes blood to clot upon the addition of some clotting agent – and the specific procedure.

To measure the clotting activity in the HLM during surgeries, traditionally, devices such as the Hemochron that rely on activated clotting time (ACT+ and ACT-LR), prothrombin time (PT), and activated partial thromboplastin (APTT) are used to guide heparin dosing. The Hemochron system utilizes single-use disposable test cartridges that contain all the necessary reagents for one of the coagulation tests mentioned above. One of the main operations performed by the Hemochron is the electrical impedance measurement, which refers to the opposition that an electrical circuit offers to the flow of alternating current (AC). When the blood clots, the electrical properties of the sample change due to the formation of fibrin networks. Specifically, the clot acts as an insulator, increasing impedance compared to the fluid state of blood[5]. Inside the disposable test cartridge, there are sensor electrodes in contact with the blood sample. As the clot forms, it affects the conductivity between the electrodes. When the blood is in its fluid state before clotting, it conducts electricity better than when it clots.

However, this approach has limitations: it consumes a portion of the patient's blood sample, does not provide real-time information on clot progression during surgery, and relies on bolus administration of heparin. The purpose of bolus injection is to rapidly achieve therapeutic anticoagulant levels. This also aids in preventing existing clots from growing larger and new clots from forming. An advantage of bolus injections is the healthcare providers' ability to calculate the exact dose based on the patient's weight and desired anticoagulation level. However, heparin's effects wear off relatively quickly after a bolus injection. If not carefully monitored, bolus doses can also lead to excessive anticoagulation, increasing the risk of bleeding. There is also the danger of rebound clotting, where the abrupt cessation of bolus heparin may lead to rebound clotting, especially if the underlying condition persists.

In contrast, we propose a novel device capable of real-time monitoring of blood clotting progression. By continuously assessing clot formation, we can tailor heparin infusion more precisely. Unlike bolus administration, which carries the risk of exceeding the minimum heparin dose required to inhibit clotting, our approach ensures optimal anticoagulation. We leverage Doppler velocimetry to gather real-time data without compromising the primary function of the heart-lung machine. To simulate the HLM environment, we construct a circuit comprising a blood reservoir, tubing, a peristaltic pump, the transducer, and a water reservoir.

A transducer is a device that converts one form of energy to another. Here, it converts pressure into an electrical signal[6]. The transducer is a critical component that emits and receives ultrasound waves from the blood flow. When these pulses encounter moving blood cells, they reflect back to the transducer. The pulser generates the electrical pulses that drive the transducer. The pulser determines the frequency of ultrasound waves emitted, usually in the megahertz range. Pulse duration and duty cycle, the ratio of pulse duration to the total cycle time, are also controlled by the pulser. The intensity of ultrasound exposure is modified by the duty cycle. The pulse also ensures precise timing between emitted pulses and data acquisition. When the reflected waves return to the transducer, they generate electrical signals. These varying voltage signals are then plotted in real-time to show their amplitude against time using the oscilloscope.

There are two main methods of extracting velocity information from ultrasound data: frequency shift analysis and phase shift analysis. The Doppler shift caused by relative motion between transducer and blood cells appears as a frequency shift on the oscilloscope display and is mathematically described in Equation 1:

$$f_d = 2f_0\frac{v}{c}\cos(\theta) \quad [1]$$

where f_d represents the Doppler shift frequency; f_0 is the transmitted transducer frequency; v is the blood velocity along the transducer beam; c is the speed of sound in the blood; and θ is the angle between the transducer and the blood flow direction. Positive Doppler shifts occur when blood cells move toward the transducer, while negative shifts indicate movement away.

In phase shift velocimetry, the movement of the scatterers, blood cells, through the ultrasound beam results in a phase shift in the echo waveform of subsequent pulses. By measuring these phase shifts (with multiple pulses very close together), distance can be calculated via Equation 2:

$$d = \frac{tc}{2} \quad [2]$$

where t is the time shift represented by the peak to peak phase shift. Then by knowing the period between pulses, the inverse of the pulse repetition frequency (f_{prf}), velocity can be calculated.

The velocity of blood flow is not uniform access the cross-section of a vessel. It is typically highest in the center and decreases towards the vessel walls, forming a parabolic profile. This is due to the viscous effects of the fluid and the no-slip condition at the vessel wall[7]. As clotting progresses, blood becomes more viscous, which in turn 'blunts' the velocity profile[8]. This bluntness serves as the metric for clot progression, thus necessitating a quantitative metric. So, once the velocity measurements are collected, a parabolic curve is fit to the data according to Equation 3:

$$V(x) = V_{max}\left(1-(1-\alpha)\left|\frac{x}{r}\right|^{\beta}\right) \quad [3]$$

where β is a metric for profile bluntness, x is position in the tube, V_{max} is the max velocity, α represents velocity at the wall, and r is the radius of the tube. This metric allows for correlation between clot progression, represented by a time since clot initiation, and the measurable velocity profile.

The objectives of this study encompassed the construction of a miniature model of a HLM and the application of ultrasound Doppler velocimetry to assess the alterations in the cross-sectional velocity profile during blood coagulation within the tubing. Specifically, two distinct methodologies, namely frequency shift and phase shift analysis, were employed for this purpose. Positioned as a proof-of-concept investigation, the study aims to furnish foundational insights crucial for subsequent investigations aimed at the development of non-invasive, continuous blood coagulation monitoring device, leveraging ultrasound Doppler velocimetry.

Materials and Methods

Development of Model HLM Flow Circuit

Flow Parameters

The flow circuit model was developed according to the design criteria of dimensional and dynamic similarity. Dimensional similarity demands all dimensions be scaled by the same factor, however as width of the tubing was the only dimension that affects flow parameters, this criterion was inherently satisfied. Dynamic similarity demands the value of dimensionless numbers to be equal, which in this case is the Reynolds number, given by Equation 4.

$$Re = \frac{\rho V_{avg} L}{\mu} \quad [4]$$

The Reynolds number was calculated from the flow parameters of a HLM model developed by Tu et. al[9], who used 0.8 mm diameter tubing and a 10 mL/min flow rate, yielding a Reynolds number of 62.5. Maintaining the Reynolds number, but scaling up the tubing diameter to provide a larger signal acquisition window, results in a tubing diameter of 1.6 mm and a flow rate of 20 mL/min.

Transducer Bracket

To ensure replicable trials, a bracket was designed in Fusion 360 to hold the transducer in a fixed position above the tubing (Figure 1). The bracket affixes the transducer at a 45-degree angle to the tubing, chosen to balance tubing wall penetration with signal acquisition. Given this angle, the hole which the tubing passes through is positioned 13.47 mm below the transducer cradle, such that the transducer's focal depth of 19.05 mm (0.75 in) coincides with the center of the tubing. The bracket was 3D printed in polylactic acid (PLA) plastic.

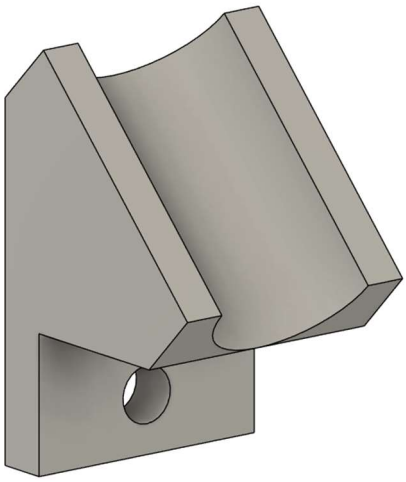

Fig. 1. Transducer Bracket. 3D model in Fusion 360 for a bracket designed to support an ultrasound transducer in the angled trough. The hole is for the tubing to go through, ensuring the tubing is at the optimal focal depth.

Assembled Circuit

The assembled circuit was composed of a peristaltic pump, a 15 mL conical centrifuge tube blood reservoir, 1.6 mm Masterflex L/S 14 tubing, and the transducer bracket affixed to a water reservoir, as the transducer needed to be immersed in water to function. The completed circuit is pictured in Figure 2.

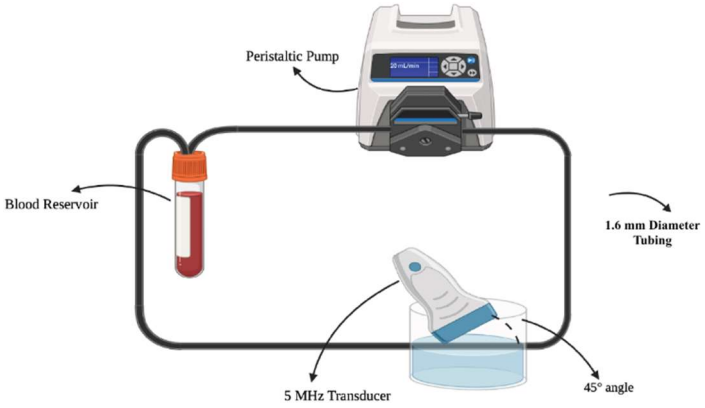

Fig. 2. Schematic Diagram of Heart Lung Machine Model Circuit. Pictographic depiction of flow circuit utilized in experimentation.

Blood and Reagent Preparation

Bovine blood was purchased from Innovative Research, anticoagulated for shipping and storage by sodium citrate mediated calcium chelation. A calcium chloride solution was prepared to recalcify the blood and permit clotting for testing. Given the blood was 0.4% citrated, a 20x concentrated solution was prepared at 400 mM in DI water. For anticoagulant testing, a 20x heparin solution was prepared at 110 IU/mL in DI water, yielding a final concentration of 5.5 IU/mL. This target concentration was calculated from the standard 300-400 IU/kg body weight heparin dosage[10] and estimating 70 mL blood/kg body weight. The relatively high solution concentrations ensured minimal dilution of the blood, to minimize factors that could influence flow dynamics.

Ultrasound Setup

Ultrasound Parameters

Parameters were chosen to satisfy Equation 5[11], derived from the Nyquist sampling theorem.

$$V_{max} < \frac{c f_{prf}}{4 f_0} \quad [5]$$

Given an expected maximum velocity (V_{max}) of ~33 cm/s, and the speed of sound in blood (c) of ~1580 m/s, a pulse repetition frequency (f_{prf}) of 5 kHz and a transducer frequency (f_0) of 5 MHz were chosen. The sampling rate was determined by the oscilloscope. For trials examining the frequency shift, a 1 GHz sampling rate was used. For trials examining the phase shift, a 0.025 GHz sampling rate had to be used to capture two subsequent pulses.

Ultrasound equipment

The ultrasound setup was composed of a Panametrics Olympus 5077PR pulser/receiver, Panametrics Olympus V309-SU immersion transducer, and Tektronix TDS 3012C oscilloscope.

Proof of Concept Testing

There were three sets of conditions for proof of concept testing: decalcified blood (stock), recalcified blood, and recalcified and anticoagulated. 7 mLs of blood was used for all trials, with 370 uL of calcium chloride solution used to recalcify the blood, and 370 uL of heparin solution used for anticoagulation. Solutions were mixed into the blood by inverting the blood reservoir 5 times, representing time 0 of the trial. The peristaltic pump was then switched on and data recording started. Data digitization was accomplished via Matlab code which stores the voltage data of each collection instance, retrieving data from the oscilloscope via GPIB connection.

Results

Frequency Shift Analysis

Preliminary Analysis

To perform frequency analysis, the time domain voltage data was converted to the frequency domain using Matlab's Fast Fourier Transform (fft) function. Frequency of the echoes reflecting off both nonmoving targets (the tubing walls) and moving targets (flowing blood cells) were analyzed in this manner (Figure 3). However, contrary to expectations, the reflection off the nonmoving wall was 3.6 MHz instead of 5 MHz. Additionally, while the flow region frequency was downshifted, the shift was much larger than expected. Given the average velocity of our flow circuit of ~16 cm/s, Equation 1 yields a frequency shift ~1 kHz. Across all trials of all conditions, as at time 0 the flow conditions are the same, the frequency echo off the wall was 4.09 ± 0.62 MHz, and the frequency of the flow region echoes was 3.21 ± 0.11 MHz. This resulted in a frequency shift of 0.89 ± 0.51 MHz, 890 times higher than expected. As a result, this frequency shift data could not accurately be equated into velocity data.

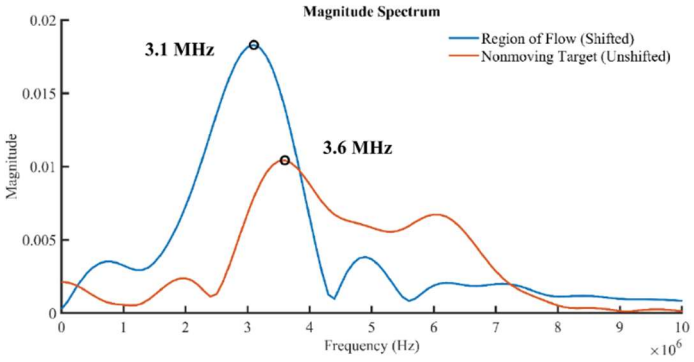

Fig. 3. Representative Frequency Magnitude Spectra. Frequency spectra for echoes received from nonmoving and moving targets. Peaks at 3.6 MHz and 3.1 MHz represent lower echo frequencies than expected.

Demonstration of Analysis Pipeline

Despite the frequency shift data not equating to real world velocity values, this section serves to demonstrate how the conversion to a velocity profile and subsequent analysis would be done. Results obtained in this section are largely for demonstrative purposes as they analyze data which did not represent realistic velocities. For demonstrative purposes, values were left as raw frequency shifts. Given the 45-degree angle of the transducer and the 1.6 mm diameter of the tubing, the angled flow depth was 2.26 mm. At a sampling rate of 1 GHz and the speed of sound in blood of 1580 m/s, this results in ~2700 samples in the flow region. The region was divided into 9 bins of 300 samples, each representing 0.168 mm of the tubes diameter when adjusting for the angle of the transducer. The peak frequency value from each bin was subtracted from the peak frequency of the wall echo to find the frequency shift. 15 seconds worth of frequency shift values at each bin depth were averaged to attenuate the effect of outliers and bins which had no detectable peak frequency. Shifts were then plotted, normalized to the max frequency shift, and fit with Equation 3 (Figure 4). Crucially, values of b, the bluntness metric, were stored for each fit.

Fits were graphed at ascending time points and their bluntness metrics were graphed against time to assess clot progression (Figure 5). For clotting induced trials, it was expected that bluntness would increase with time as the blood became more viscous as a result of clotting. However,

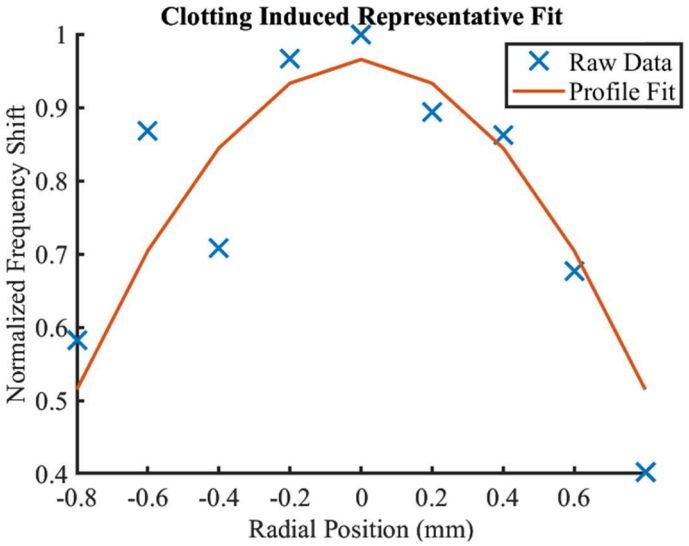

Fig. 4. Example Velocity Profile Fit. Frequency shift values normalized to the max shift, for clotting induced trial at time point 2 minutes. Fit to equation X2 with parameters Vmax = 0.965, a = 0.533, b = 1.90, and an r^2 = 0.78.

when linear regressions were performed, no positive slope was observed. For the anticoagulated blood it would be expected that over a short time frame, such as 5 minutes, that bluntness wouldn't increase significantly. As evidenced by r^2 values ranging from 0.01 to 0.59 for the displayed fits, bluntness metric values fit to the data were of low quality. However, despite the low quality data, this method demonstrates the ability to determine a velocity profile with a radial spatial resolution of 0.168 mm every 15 seconds, and quantitively assess the bluntness of the profile.

Phase Shift Analysis

Preliminary Analysis

To perform phase shift analysis, data had to be acquired from two subsequent pulses. Given a pulse repetition frequency of 5 kHz, pulses were spaced 0.2 millisecond apart. The code used to digitalize the data only captured 1 instance of the oscilloscope readout every 0.5 seconds. Thus, it was necessary to adjust the window of the oscilloscope to capture greater than 0.2 millisecond, which in the case of the settings of this oscilloscope was 0.4 millisecond. This adjustment decreased the sampling rate from the 1 GHz used in the frequency shift analysis to 0.025 GHz, a 40 fold decrease. This decrease in sampling rate led to poor reconstruction of the waveforms, despite still exceeding the Nyquist frequency (Figure 6). Some slight phase shifts are visible within the two subsequent pulses; however, the jagged nature of the waveforms obfuscated apparent shifts.

Demonstration of Analysis Pipeline

Despite the poor waveform reconstruction, analysis was still performed to demonstrate the conversion of the data into a velocity profile. Peaks within the waveform were found using Matlab's findpeaks function. The indices of these peaks were compared to pair the peaks between the 2 waveforms. Indices of paired peaks were subtracted to determine the index distance between them, representative of the phase shift. These index differences were converted to time shifts by dividing by the sampling rate of 0.025 GHz. The time shifts were converted to position shifts by Equation 2, before dividing by the time between pulses, 0.2 milliseconds, to determine velocity. Radial position information was encoded in the positions of the peaks. Position vs velocity was graphed

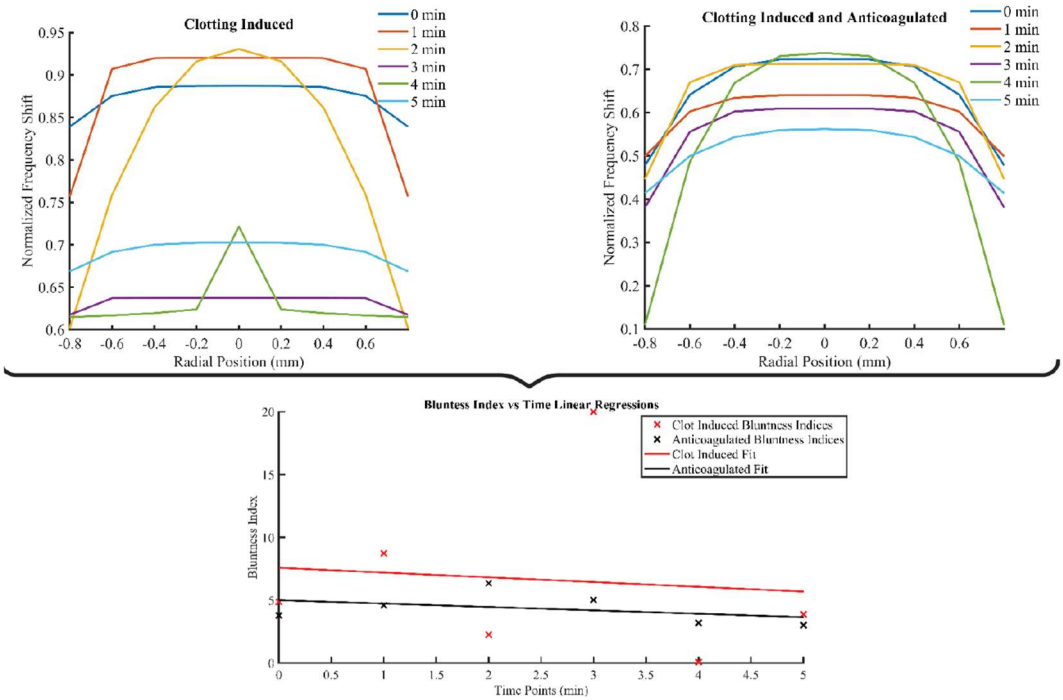

Fig. 5. Comparison of Profile Fits and Bluntness Metrics for Clotting Induced and Anticoagulated Trials. Fits for normalized frequency shift (shift/max shift) vs radial position ($0.01<r^2<0.59$) and linear regressions for bluntness metric vs time point for clot induced and anticoagulated blood over a 5 minute span (slopes = -0.38, -0.27 respectively). Non positive slopes indicate no increase in bluntness over time for either anticoagulated blood, which is as expected, nor clotting induced blood, a deviation from expectations.

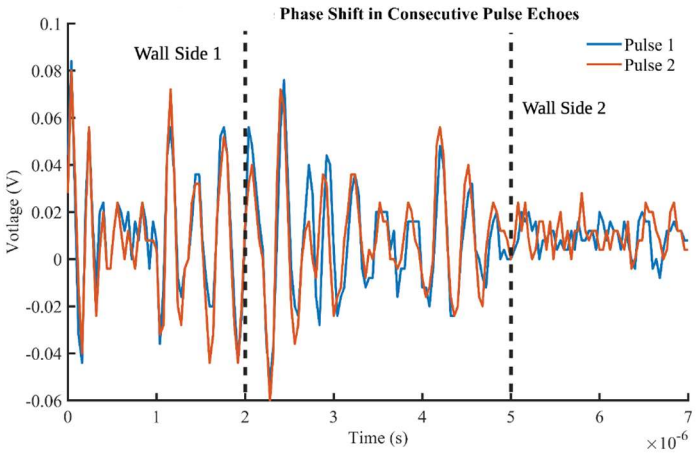

Fig. 6. Phase Shift in 2 Subsequent Pulses. Overlay of 2 subsequent pulses, 0.2 milliseconds apart, to demonstrate phase shift. Phase shifts were inconsistent. Sampling rate of 0.025 GHz led to poor waveform reconstruction.

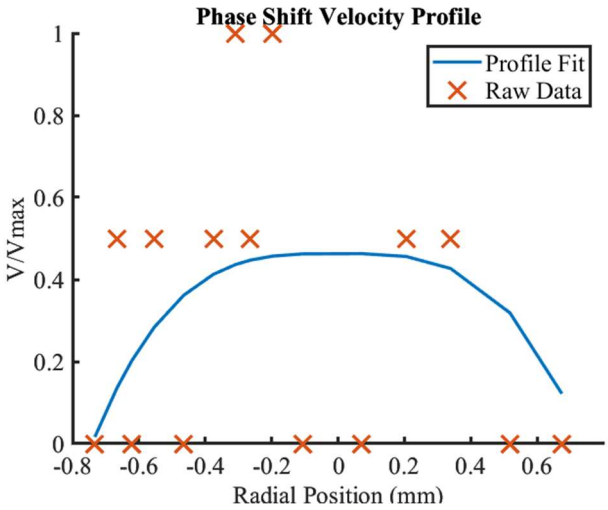

Fig. 7. Velocity Profile Fit to Phase Shift Derived Velocities. Overlay of 2 subsequent pulses, 0.2 milliseconds apart, to demonstrate phase shift. Phase shifts were inconsistent. Sampling rate of 0.025 GHz led to poor waveform reconstruction.

and a fit attempted using the same method as described in the frequency shift analysis (Figure 7). However, the raw data, while vaguely parabolic, was distorted by several points where no phase shift was detected, resulting in a calculated velocity of 0. This resulted in an r^2 value of 0.167, indicative of a poor fit.

Low Sampling Rate as a Cause of Poor Quality Data

To validate the hypothesis that the poor sampling rate and resultant poor waveform reconstruction contributed to the resultant poor velocity data and profile fit, simulated data was analyzed. Idealized simulated data was designed by assuming a maximum shift at the center of the flow region and no shift at the walls. Equation 6 was used to generate sinusoidal data with these parameters over the approximately 3 microseconds span of the

$$\sin(2\pi f t + 2.2tE6) \quad [6]$$

ultrasound echo travel time in the flow domain. Simulated data was generated at sampling rates of 0.025 GHz, the rate used in the above phase shift analysis, and 1 GHz, the rate used in the frequency shift analysis (Figure 8a). The data generated with the low sampling rate was similarly jagged as expected which resulted in a similarly vaguely parabolic velocity data. Poor velocity resolution was seen in both the simulated and real data as only 3 velocity values were present. This stemmed from the low sampling rate, as the differences between paired peak indices were either 0, 1, or 2. In contrast, the higher sampling rate simulated data had more samples which provided a more granular difference in indices, which was reflected in the numerous velocity values interspersed between the 3 values present in the low sampling rate data. The resultant velocity profile fits (Figure 8b) and their r^2 values of 0.679 and 0.983 for the 0.025 GHz and 1 GHz sampling rate data respectively reflected the importance of greater velocity resolution.

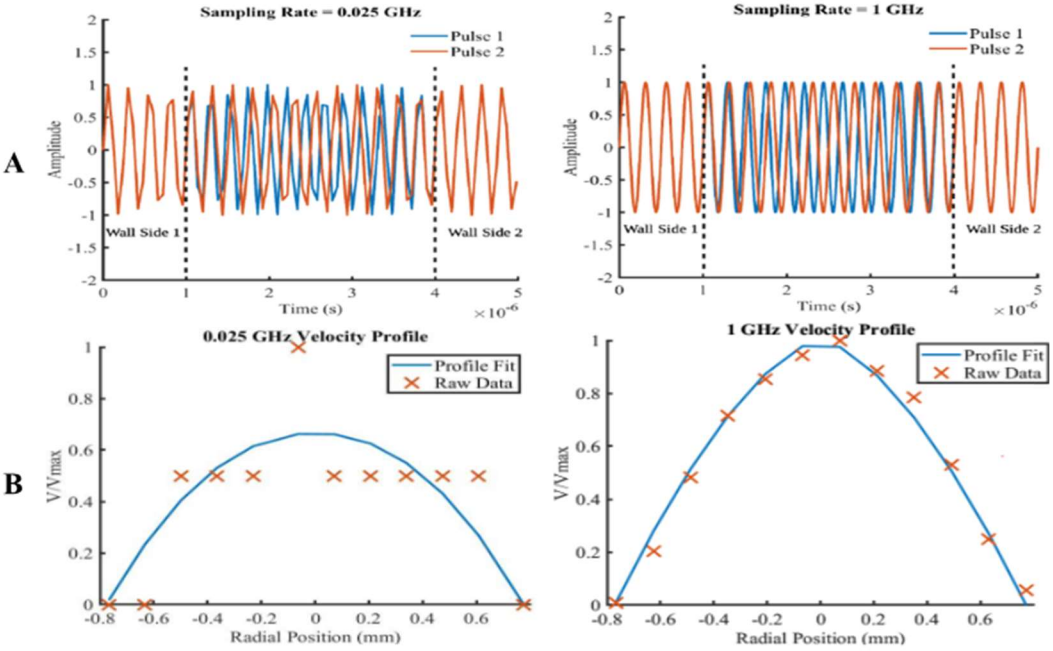

Fig. 8 Effects of Sampling Rate on Waveform Reconstruction and Velocity Profile Fitting. (A) Simulated wave forms of idealized sinusoid data at experimental sampling rate (0.025 GHz) and ideal sampling rate (1 GHz). Poor reconstruction at the lower sampling rate led to a jagged waveform. (B) Velocity profile fits to velocity data extracted from the peak to peak phase shift from subsequent pulses. Poor velocity resolution because of low sampling rate resulted in poorer fit, with r^2 = 0.679 and 0.983 in the 0.025 GHz and 1 GHz sampling rate data respectively.

Discussion

The frequency analysis conducted in this study aimed to characterize the reflection of ultrasound echoes from both nonmoving targets, such as tubing walls, and moving targets, like flowing blood cells. Surprisingly, the frequency of the echoes off the nonmoving wall differed significantly from expectations, registering at 4.09 ± 0.62 MHz, instead of the anticipated 5 MHz. Moreover, the frequency shift observed in the flow region was substantially larger than predicted, with an average shift of 0.89 ± 0.51 MHz, significantly higher than the expected shift of approximately 1 kHz based on the average flow velocity. This discrepancy rendered the frequency shift data unreliable for translating into velocity data, highlighting a potential limitation in the accuracy of the method in the need for a extremely narrow banded pulser in order to extract minute frequency shifts.

Despite the inability to accurately convert frequency shift data into velocity values, the analysis pipeline demonstrated in this study provides valuable insights into the methodology for future studies. By presenting a step-by-step demonstration of the conversion process to derive a velocity profile, the study underscores the potential of the approach, albeit with limitations. Notably, the spatial resolution achieved, with measurements taken at intervals of 0.168 mm, offers a detailed view of the flow dynamics within the tubing. However, the effectiveness of this method was hampered by the low quality of data, particularly evident in the poor fitting of bluntness metrics to clot progression data, indicating room for improvement in future experimental setups and data processing techniques.

The phase shift analysis, although hindered by the low sampling rate, provided additional insights into the velocity profile determination process. Despite challenges in waveform reconstruction and subsequent data analysis, the method demonstrated the feasibility of deriving velocity information from phase shifts between ultrasound pulses. However, the poor quality of the data, characterized by low r^2 values and distorted velocity profiles, underscores the critical role of sampling rate in obtaining accurate velocity data. Overall, the study highlights the importance of considering sampling rate and waveform reconstruction in ultrasound-based velocity analysis, emphasizing the need for further refinement of experimental techniques to enhance the accuracy and reliability of results in future studies. One such way to do this is the implementation of a sampling board in place of data digitalization from an oscilloscope., ideally with a sampling rate around 1 GHz.

Future Work

There is still much to be done to demonstrate the accuracy and viability of the described methods. Primarily, data must be collected via these methods which show the literature described phenomenon of clot progression correlating with profile bluntness. Additionally, correlation between the bluntness metric for clot progression and an established metric, such as ACT, would demonstrate the validity of the method. Finally, development of a model which determines dosage adjustments to a continuous heparin infusion in response to changes in profile bluntness is necessary for the final development of a potential device. This model would work with the same principle as an insulin pump, leveraging a negative feedback control system to maintain profile bluntness, and thus clot progression, at a level safe for the patient throughout the surgery.

End Matter

Author Contributions and Notes

Khairandish, B., and Arpin, W. designed research, performed experiments, analyzed data, and wrote the paper. The authors declare no conflict of interest.

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William Arpin

Spring, 2024

On my honor, I have neither given nor received any unauthorized aid on this assignment as defined by the honor guidelines for thesis related assignments

Advisor

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Introduction

Cardiovascular diseases (CVDs) were the top global cause of death in 2019, responsible for 32% of all fatalities (WHO, 2021). A 2019 report by the American Heart Association revealed that nearly half of adult Americans had CVD (AHA, 2019). These statistics make it abundantly clear that everyone of us likely has, will have, or knows someone who has some form of CVD. These numbers have been rising recently, partly due to changes in CVD diagnosis and unhealthy modern lifestyles: poor diets, physical inactivity, tobacco/alcohol abuse, stress, and subpar environmental conditions (AHA, 2019; WHO, 2021).

In addition, the brunt of these diseases are often borne by minority groups. For example, studies have shown that black Americans are more than twice as likely to die of a CVD compared to their white counterparts. These staggering statistics have been linked to structural racism, widespread practices and institutions within a society which favor certain racial groups, resulting in minorities having higher exposure to various CVD risk factors (Javed et al., 2022, p. 76).

Lower average socioeconomic status is the main driver of this inequality as it leads to minorities living in lower income neighborhoods. This in turn makes it more difficult to obtain healthy foods and maintain an active lifestyle due to food deserts, areas where healthy food options are unaffordable or absent, and lack of outdoor recreational spaces respectively (Kelli et al., 2019, p. 10). Additionally, lower income areas often are exposed to higher levels of pollutants, another driver of CVD (Javed et al., 2022, p. 76). Furthermore, overt discrimination, or even just the perception of it increases the risk of CVD development as a result of the increased stress (Banerjee et al., 2021, p. 166; Javed et al., 2022, p. 76).

Critically, even when minorities are able to gain access to healthcare, biases in how care is distributed and administered often limit their access to the treatments they need. The consequences of this are existential, as an already incredibly destructive class of diseases is affecting and killing minorities at disproportionate rates.

Even those fortunate enough to not experience this inequity are nevertheless indirectly affected. CVDs place a large resource/financial burden on the healthcare industry and the economy as a whole through lost productivity (Benjamin et al., 2018, p. 102). This is a systemic and difficult to solve issue, especially within American society. However, understanding the extent of racial biases, both human and machine, and mitigating their effects through education and ethical design is one step we can take to make healthcare more equitable.

There are two main ethical frameworks to be considered in clinical decision making, deontological and utilitarian. The deontological framework serves as the basis for ideals such as the Hippocratic Oath (Kapocsi & Jenei, 2003). It is the idea that regardless of the outcome, doing harm to or neglecting the patient is never justified (Mandal et al., 2016, p. 6). Ideally, this would be the only framework needed in medicine, however we live in a world of finite resources. As a result, the utilitarian framework is of great importance, especially in resource scarce hospital settings. Utilitarianism is the idea that resources should be distributed to maximize the good done (Mandal et al., 2016, p. 6). In clinical settings this can present as a patient with a higher post operational life expectancy receiving an organ transplant over another older or sicker patient. Balancing these frameworks is critical for hospital functionality, however racial biases can result in behavior that violates these ethics.

Bias in Healthcare

Implicit racial bias is prevalent within healthcare professionals, at rates similar to the wider population (FitzGerald & Hurst, 2017, p. 13), with several studies finding anti-black bias in roughly 40 percent of clinicians (Hall et al., 2015, p. 65). When this bias influences decisions regarding distribution and quality of care ethical breaches and loss of healthcare equity occur.

One common area that biased decisions manifest is in high stress situations, such as emergency medicine (Johnson et al., 2016, p. 6). The need to make quick and complex decisions can lead to a reliance on heuristics, such as implicit biases. For example, in the cardiac field, minorities often experience longer wait times for time sensitive diagnoses, such as via angiogram, and treatments, such as life saving thrombolytics (clot dissolvers) (Banerjee et al., 2021, p .167). While it is difficult to directly attribute this to implicit bias, as the practitioners from this study did not take an implicit bias test, it is clear there is a significant driving force affecting distribution of care despite controlling for economic and other outside factors.

Situations such as these represent failings of both utilitarian and deontological ethics. By favoring the timely treatment of white patients over that of minorities, resources are not being utilized in the way to do the most overall good. Additionally, by making patients wait longer based on their race, clinicians are breaching the deontological principle by neglecting the patient's care.

However, even in less stressful situations, allowing practitioners more time for careful judgment, there is still significant bias. For example, AICDs are implantable defibrillators which greatly prolong life in cardiac arrest survivors, however eligible black men are only 74 percent as likely to receive one compared to an eligible white man, after adjusting for all outside factors (Capers & Sharalaya, 2014, p .172). Eligibility is typically determined by the risk for sudden

cardiac death (SCD), which black people have the highest lifetime risk for (Kiernan et al., 2022, p. 808). This can partially be attributed to the fact that majority black hospitals tend to have less access to cardiac specialists, however even when black patients have access, they are still less likely to undergo AICD implantation (Kiernan et al., 2022, p. 813). Providers, physicians and specialists recommending AICD implantation, rarely exhibited explicit bias, however implicit biases were measured (Kiernan et al., 2022, p. 813). Additionally, black patients rated implicitly biased physicians lower in terms of patient-physician interaction, which can have a negative impact on trust, potentially leading to the patient rejecting a treatment recommendation. Furthermore, preimplantation counseling results in the majority of patients accepting AICD implantation, regardless of race. However, minority patients are less likely to receive this counseling compared to white patients (Kiernan et al., 2022, p. 813). Once again we see a deontological failing as racial biases influence the practitioner's behavior, resulting in suboptimal care.

Bias Exacerbation in Medical Education

With racial bias being this prevalent and impactful in health, it is critical to manage its effects wherever possible. Implicit biases are known to emerge early in childhood development, appearing strongly and consistently in children as young as 10 years old (Dore et al., 2014, p. 223). However, while the foundation for bias forms early in life, steps can still be taken to limit its further development. One critical area to target, specifically for the healthcare sector, is the curriculum in medical schools. The current mainstream curriculum reinforces the concept of racial biological differences, building upon previously formed biases and potentially forming new ones (Tsai et al., 2016, p. 918).

One way by which this association occurs is through generalizing many genetically distinct groups under one race. For example, “black” is the common term used to refer to people of African descent, however within this grouping there are vast genetic differences. In fact, with the current groupings commonly used, there are more genetic differences within groups than between them (Agyemang et al., 2005, p. 1014). So, when these broad categories are used instead of the precise genetic distinctions that can actually predispose groups to various diseases, students can form false associations between race and disease.

Furthemore, these associations can also form when educators indicate race derived differences in disease prevalence without explaining the structural racism that leads to it. For example, as previously discussed, African Americans are at a higher risk for CVDs, but this is not the result of biological differences, rather the societal structures which perpetuate poor health and living conditions. However, this critical context is rarely emphasized in medical schooling (Amutah et al., 2021, p. 873).

This can have the effect of associating certain races with certain diseases, which can lead to diagnostic bias (Amutah et al., 2021, p. 875). This bias can present, for example, as a reluctance to diagnose a black patient with a so-called ‘white disease’, or a compulsion to diagnose them with a ‘black disease’. This constitutes a breach of the aforementioned deontological ethical framework. By putting the patient into this category, the practitioner is not doing their due diligence to correctly diagnose their patient, ensuring they get the proper treatment. Instead they are taking a cognitive shortcut, potentially putting the patient’s health at risk via a non or incorrect diagnosis.

Additionally, the associations formed in medical school can make it easier to accept the race based resource distribution algorithms that are taught to students and used in the industry

(Amutah et al., 2021, p. 875). These algorithms are primarily designed to assist clinicians in resource allocation and decision making, however race based adjustments skew their accuracy. For example, the AHA's heart failure risk calculator takes applicable information, such as age, blood pressure, cholesterol level, and relevant medical history to determine a risk score used to help determine how urgently care is needed. However, it also has a 'black' option which decreases the overall risk score (Vyas et al., 2020, p. 874). This largely unjustified addition can direct care away from black patients as they will be perceived as lower risk than white counterparts presenting the same symptoms. By misappropriating resources away from those at equal or greater risk, these guidelines represent a utilitarian ethical failure.

Approaches to Mitigate Bias

In order to limit the formation of race based associations during this critical time of learning, the curriculum must be altered. Firstly, the National Academy of Medicine (NAM) recommends using more precise language and categorization pertaining to ancestry rather than race (Medicine et al., 2009). Using more specific categories, such as country of origin, highlights the genetic differences that actually drive biological variation. Additionally, if discussing race based prevalence statistics, the curriculum should stress the driving factors behind these differences. Namely the socioeconomic factors that often predispose minority individuals to various diseases. Finally, removing race adjusted algorithmic guidelines from the curriculum. These algorithms often either feature no explanation for their adjustments, or they are based solely on empirical correlations (Vyas et al., 2020, p. 874). Even this second category is problematic as the adjustments are made on the assumption that race correlates with genetic differences (Vyas et al., 2020, p. 874), however there is wide genetic variation within racial

groupings as previously discussed. Adjustments should be based on known biological factors, not social constructs, and thus removing these baseless adjustments within the curriculum should help alleviate bias formation.

Implicit biases are within all of us to some extent, and they are very difficult to alter. In fact, interventions simply targeted at helping subjects identify their bias and attempting to reduce it have largely failed. While interventions such as counter-stereotype imaging (imagining people in roles not conducive to stereotypes) and taking the perspective of minorities present have managed to immediately reduce implicit bias, they fail to achieve long term change (Vela et al., 2022, p. 6). Thus, it is the goal of recent interventions not only to reduce implicit biases, but to give practitioners the tools and skills to manage their bias.

These recent approaches are built upon the concept of transformative learning theory (TLT). TLT is all about altering a subject's existing frame of reference by disrupting their assumptions, prompting critical self reflection, and engaging in guided dialogue (Mezirow, 1997, p. 6). First, educators must provide subjects with information or an experience that challenges their implicit biases. For example, demonstrating a disease is not 'black', but that socioeconomic factors predispose black people to develop the disease at higher rates. Next, helping subjects identify implicit bias within themselves, such as through the racial implicit association test, and prompting them to reflect on how this bias has shaped their past actions. Finally, engaging in group dialogue to discuss ways to manage bias in practice. TLT stresses the importance of letting the subjects draw these conclusions, with the educators merely acting as mediators of discussion, not driving it (Gonzalez et al., 2020, p. 8). The final step that goes beyond just education and theory is to actually put this into practice. Several recent studies have accomplished this through play acting scenarios, resulting in significantly higher rates of self reported confidence in dealing

with bias scenarios (Gonzalez et al., 2020, p. 8; Wu et al., 2019, p. 22). TLT in combination with practical skills based learning has shown early promise, but there is still much to be studied regarding the approach.

Bias in Artificial Intelligence

While striving to reduce bias in healthcare practitioners is of high importance, it should be noted the difficulty in altering human psychology. One potential workaround is the use of artificial intelligence (AI) to assist in clinical decision making. This would essentially reduce the human impact, thereby reducing the ability for bias to influence decision making. There are a number of algorithms already in use in cardiac healthcare. They can provide fast and accurate analysis of the many diagnostic tests used in the field from ECG data points to MRI images (Sun et al., 2023, p. 2). However, these proposed AI programs can harbor biases themselves, so-called machine bias. This bias can arise at multiple different stages of AI model development, potentially even cascading through and intensifying the biased response.

At the most basic level, bias can be introduced by model developers who fail to consider the aforementioned systemic biases that lead to such disparities in healthcare. Large scale resource management algorithmic models are especially vulnerable to this pitfall. Their inherent general use for resource allocation across a range of ailments almost necessitates a proxy by which to measure a patient's health. In many cases, this proxy is future healthcare costs, as not only does cost strongly correlate with need, but the goal of these algorithms is to reduce future cost (Obermeyer et al., 2019, p. 449). Thus, in a vacuum, it makes sense to provide the most aid to patients with the highest predicted future healthcare costs. However, as a result of systemic barriers to healthcare, minority groups spend less on healthcare than their white counterparts

(Obermeyer et al., 2019, p. 449). So, when one widely used algorithm, which was trained on race-blind data, was built with cost as its health proxy, it was found to severely underallocate increased aid to black patients (Obermeyer et al., 2019, p. 449). So much so that when the algorithm was fed a dataset adjusted to have no race based predictive cost gap, the percent of black patient's automatically recommended for increased care rose from 18% to 47% (Obermeyer et al., 2019, p. 449). By overlooking the systemic issues which have led to a socioeconomic racial divide, the designers introduced bias into an otherwise race blind algorithm. As a result, this algorithm breaches the utilitarian ethics it was designed to promote. Instead of distributing resources to those with the greatest health needs, it instead directed aid in a manner to equalize predicted future healthcare expenditures. However, this only serves to exacerbate the health disparity already present. Instead, algorithmic design must be socially informed. If the very basis of the design is already prone to bias as a result of real world factors, this will propagate through the rest model, skewing the results. AI developers have to be socially conscious, which can be enabled through diversifying development teams. Racial diversity can offer new perspectives, potentially catching these baked in bias problems before they can be incorporated into the model. Additionally, diverse professional perspectives, such as that from sociologists or specific experts in the study of systemic bias, should be incorporated into the design process.

Bias in Training Data

Some of the most prevalent and often discussed sources of bias come from the data collection and processing performed to build the large datasets required to train these models (Nazer et al., 2023, p. 2). In order to build a machine learning model, large datasets must be used

to ‘train’ the model. Simply, the model uses this data to identify patterns between variables in order to make outcome predictions when later supplied with similar data (*Machine Learning, Explained | MIT Sloan*, 2024). Selection of this training data is crucial for model development, with biases in the training data propagating into a biased prediction model.

Sampling bias occurs when the dataset is not representative of the population. This is a very common problem as datasets often over represent white populations while underrepresenting minorities. Once again, this often arises from aforementioned systemic barriers to equitable healthcare access. As this data is often sourced from hospital settings, when minorities are disproportionately receiving less care, they correspondingly appear disproportionately less in collected data. For example, in out of hospital cardiac arrest cases, one of the primary determinants of if the patient is able to survive long enough to reach a hospital, is administration of CPR. Patients who unfortunately die before entering the healthcare system will not be entered into datasets that may later be used to train models related to predicting heart attacks. So, the results of one study that found black and hispanic patients received CPR at lower rates than white counterparts, propagates into less data available for these demographic groups (Garcia R. Angel et al., 2022, p. 1569). This is just one example of the countless barriers that minorities face which limit their representation in datasets. This ties into a phenomenon called overtraining, in which the algorithm is only able to accurately assess data similar to the training data. Thus, if the training data does not contain data representative of minority groups, the algorithm’s accuracy will suffer when presented with such data.

Another similar source of bias is known as labeling bias, which occurs when the outcome variable is determined differently between different, in this case racial, groups (Paulus & Kent, 2020, p. 1). For example, one study found that the rates of echocardiogram use, an ultrasound

based technique used to diagnose various cardiovascular diseases, were lower for black patients compared to white patients (Hyland et al., 2022, p. 956). As has been discussed this is a common trend across a variety of diagnostic measures. This most likely stems from a variety of the previously discussed systemic factors. For example, the AHA's risk score calculator returning lower risk values for black patient's would limit the amount of further screening they undergo. Additionally, lower trust in doctors, hospital overcrowding and under resourcing in predominantly black areas, and lower socioeconomic class are all barriers to these more specialized screening methods that are so often used to train algorithms. Similarly to sampling bias, labeling bias can result in a model falsely correlating minority populations with lower rates of occurrence of CVDs as there is disproportionately less data, despite higher rates of CVDs in actuality. This in turn can bias the algorithm to recommend higher rates of screening for white patients as they are perceived to be at a higher risk.

These are just two examples of potential sources of bias in data collection, but one thing is common across these biases: they are derived from the already existing systemic bias within the healthcare system. This is not a fault of coding or model development, but rather of the system. As a result, the most effective way to mitigate this source of bias would be to address the root cause, however due to the difficulty of this, this paper will focus on the more practical approach of treating the 'symptoms'.

One simple method is to simply acknowledge the limitations of a model. Not every model must be largely generalizable to every population. In fact it would be unethical to claim generalizability for a model trained on a biased data set. Inaccuracy for minority populations would violate deontological ethics at the patient level, when models are utilized to provide individual diagnoses, as this inaccuracy would lead to a suboptimal level of care. And on a

logistical level, inaccuracies would lead to inefficient allocation of resources, away from the minority populations, regardless of their level of need. Thus, setting guidelines to only allow for use on populations that the algorithm can accurately predict is crucial. However, this strategy must be paired with a focus on developing such specific models not only for white populations, but also for minority populations, in order to ensure equitable access to these algorithms. In a world with limited access to minority health databases, one way this could be accomplished is through open source coding (Norori et al., 2021, p. 1). By allowing predominantly minority hospitals access to the code by which these algorithms are trained, they could train their own local AI with their own data. This AI would not be a generalizable tool, but rather tailored to the demographics of the specific institution.

Bias in Model Development

One intriguing but potentially problematic aspect of machine learning is the so-called 'black box' that the algorithm learns in. This means that it can be hard to tell exactly how the algorithm actually finds patterns and correlations used to make its predictions. As a result, if precautions are not taken to prevent unintended parameters from impacting the outcome, the algorithm can fall victim to 'shortcut learning'. For example, in algorithms trained to examine medical images, parameters such as image size, orientation, and the instrument used to capture the image can be misidentified by the model as relevant information (Trivedi et al., 2022, p. 2). If, for example, data sourced from a predominantly black hospital which used a certain type of imaging device is combined with data from a white hospital which uses a different imaging device, the algorithm can derive this racial signal. Then, if the data is skewed such that images captured from one device are more likely to be disease positive, the algorithm can take the

shortcut to associate images from said device to be disease positive, and thus the race that is associated with that device in the dataset (Zou et al., 2023). Shortcut learning is difficult to detect and mitigate, however feature disentanglement: a process to punish the algorithm for identifying these uninformative patterns has shown some initial success (Trivedi et al., 2022, p. 3).

Conclusion

Implicit and systemic racial biases are the unfortunate reality of our healthcare system. In the cardiovascular field especially, where many minority groups have higher risk of incidence and death, these biases have a large negative impact on the equitability of care. Implicit biases are present on some level in every individual, however problematic practices in the medical education field exacerbate biases. Using more granular ethnic categorizations that more accurately reflect genetic differences, teaching students about the systemic factors that drive differential rates of disease incidence, and removal of erroneously race adjusted guidelines from medical education is critical to mitigating the further development of bias. Additionally, recent studies in Transformative Learning Theory have shown progress in the long term mitigation of bias in adults. Utilization of algorithms is not the panacea to bias in healthcare that it may first appear to be. Uniformed design of inputs, biases in how the datasets used to train these algorithms are collected, and unforeseen off target shortcut learning can propagate real world biases into these algorithms, skewing their accuracy.

These biases, both human and machine, have grave ethical implications. On the individual level, deontological ethics demands healthcare practitioners perform to the best of their ability for all patients. When practitioners allow biases to skew their decision making, be it in diagnosis or treatment plan, they no longer follow the ethical framework that serves as the

basis for modern healthcare. Practitioners must provide equitable and, to the best of their ability, accurate and effective care. Algorithms made to assist practitioners in diagnosis and treatment must also perform accurately for all racial demographics. On a logistical level, another important consideration for the modern hospital, utilitarian ethics requires distribution of care and resources in a way that performs the most overall good. This requires the accurate assessment of risk and healthcare needs, which is increasingly being made by algorithms. Designers of these algorithms must ensure accuracy to avoid perpetuating the inequitable distribution of care that has led to dataset biasing in the first place. Major steps must be taken, but mitigation of human bias, and ethical development of algorithms offer a promising path forward for ensuring a more equitable and ethical healthcare industry.

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Analysis of the Use of Algorithmic Automation and Racial Bias within Healthcare

(STS Topic)

Development of a Novel Clot Monitoring Device for Cardiopulmonary Bypass

(Technical Topic)

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On my honor, I have neither given nor received any unauthorized aid on this assignment as defined by the honor guidelines for thesis related assignments

Introduction: Cardiovascular diseases (CVDs) were the top global cause of death in 2019, responsible for 32% of all fatalities (WHO, 2021). A 2019 report by the American Heart Association revealed that nearly half of adult Americans had CVD (AHA, 2019). These statistics make it abundantly clear that everyone of us likely has, will have, or knows someone who has some form of CVD. These numbers have been rising recently, partly due to changes in CVD diagnosis and unhealthy modern lifestyles: poor diets, physical inactivity, tobacco/alcohol abuse, stress, and subpar environmental conditions (AHA, 2019; WHO, 2021).

In addition, the brunt of these diseases are often borne by minority groups. For example, studies have shown that black Americans are more than twice as likely to die of a CVD compared to whites. These staggering statistics have been linked to structural racism, widespread practices and institutions within a society which favor certain racial groups, resulting in minorities having higher exposure to various CVD risk factors, like those mentioned above (Javed et al., 2022). Critically, even when minorities are able to gain access to healthcare, biases in how care is distributed and administered often limit their access to the treatments they need. This can especially be seen when resources are scarce, as, for example, black people are seen as lower risk by AHA's heart failure risk calculator (Vyas et al., 2020, p. 874). The consequences of this are existential, as an already incredibly destructive class of diseases is affecting and killing minorities at disproportionate rates.

Even those fortunate enough to not experience this inequity are nevertheless indirectly affected. CVDs place a large resource/financial burden on the healthcare industry and the economy as a whole through lost productivity (Benjamin et al., 2018). This is a systemic and difficult to solve issue, especially within American society. However, a combination of proper

trained healthcare algorithmic automation and worker education has the potential to at least reduce inequities within healthcare.

Moreover, even accessible treatments can be costly and perilous. Procedures like open-heart surgery, employing cardiopulmonary bypass machines, often result in postoperative bleeding due to necessary anticoagulants (Shuhaibar et al., 2004, p. 947). Severe, life threatening bleeding can occur, but even controllable bleeding puts a large strain on hospitals and patients, with transfusions consuming as much as 25 percent of blood products (Woodman & Harker, 1990, p. 1680). To mitigate bleeding, we propose continuous heparin infusion, ensuring precise dosing compared to the current bolus technique. This approach is facilitated by a device continuously monitoring clot progression, allowing for adjustments to the infusion dosage. Such innovations promise to enhance patient outcomes and alleviate the burden on healthcare resources associated with CVD treatments using cardiopulmonary bypass machines. In turn, by alleviating the strain on resources, this device can help to lessen at least one factor, resource scarcity, which often leads to inequitable treatment. Albeit this is merely treating an upstream problem, whereas true change must come from addressing the root causes of bias.

STS Topic: A variety of factors derived from structural racism predispose minority groups to CVDs. Lower average socioeconomic status is the main driver of this inequality. It leads to minorities living in lower income neighborhoods, which in turn makes it more difficult to obtain healthy foods and maintain an active lifestyle due to food deserts and lack of outdoor recreational spaces respectively (Kelli et al., 2019). Additionally, lower income areas often are exposed to higher levels of pollutants, another driver of CVD (Javed et al., 2022). Furthermore,

overt discrimination, or even just the perception of it increases the risk of CVD development as a result of the increased stress (Banerjee et al., 2021, p. 166; Javed et al., 2022).

With the deck already stacked against minority groups, it's critical that they are at least able to access the care they need. However, even if healthcare is financially accessible, implicit biases within the industry often result in worse/less treatment for minorities compared to white people. For example, minorities often experience longer wait times for time sensitive diagnoses, such as via angiogram, and treatments, such as life saving thrombolytics (clot dissolvers) (Banerjee et al., 2021, 167). While it is difficult to directly attribute this to implicit bias, as the practitioners from this study did not take an implicit bias test, it is clear there is a significant driving force affecting distribution of care despite controlling for economic and other outside factors.

Even in seemingly clear cut situations where there's less time pressure, giving practitioners time to make more careful decisions there's still significant bias. For example, AICDs are implantable defibrillators which greatly prolong life in cardiac arrest survivors, however eligible black men are only 74 percent as likely to receive one compared to an eligible white man, after adjusting for all outside factors (Capers & Sharalaya, 2014, p. 172). Eligibility is typically determined by the risk for sudden cardiac death (SCD), which black people have the highest lifetime risk for (Kiernan et al., 2022, p. 808). Specifically for AICD implantation, this is often determined by the ejection fraction, the percentage of blood pumped out of your heart with each beat, where less than 30 percent is the common threshold (Capers & Sharalaya, 2014, p. 172).

There are three major barriers to equitable AICD uptake, the patient, the provider, and the system. The patient has a right to refuse a recommended treatment, and in one study 20 percent

of black people refused an AICD compared to only 7 percent of white people (Kiernan et al., 2022, p. 813). This can result from many factors such as historical medical mistreatment of minorities leading to low trust, and lack of knowledge of the procedure. The effect of procedural knowledge was tested in one study which found that an educational video shown to patients increased the rate at which black people will approve of an AICD implant, however this was not enough to fully close the gap in implantation rates among whites and blacks (Thomas et al., 2013, p. 157). Providers, physicians and specialists recommending AICD implantation, rarely exhibited explicit bias, however implicit biases were measured (Kiernan et al., 2022, p. 813). Additionally, black patients rated implicitly biased physicians lower in terms of patient-physician interaction, which can have a negative impact on trust, potentially leading to the patient rejecting a treatment recommendation. Furthermore, preimplantation counseling results in the majority of patients accepting AICD implantation, regardless of race. However, minority patients are less likely to receive this counseling compared to white patients (Kiernan et al., 2022, p. 813). At a systems level, black patients are more likely to receive care at majority black patient hospitals, which typically have lower access to cardiovascular specialists. However, even at these majority black hospitals, white patients are more likely to undergo specialized cardiac procedures (Kiernan et al., 2022, p. 812).

On top of all this, many practitioners are either unaware of or deny care disparity at their clinical location (Sotto-Santiago et al., 2021, p. 697). This all results in a situation where minorities are more likely to develop a cardiovascular disease and not receive sufficient treatment, resulting in higher death rates.

It is clear there is a human failing at play here, prompting one to ask, what if we simply delegated this task to machines? There are a number of algorithms already in use in cardiac

healthcare. They can provide fast and accurate analysis of the many diagnostic tests used in the field from ECG data points to MRI images (Sun et al., 2023, p. 242). However, there are a few factors which make these algorithms prone to bias themselves. The first, and most incomprehensible, is racial based scoring adjustments, such as the one present in the AHA's heart failure risk score calculator. This calculator takes applicable information, such as age, blood pressure, cholesterol level, and relevant medical history to determine a risk score used to help determine how urgently care is needed. However, it also has a 'black' option which decreases the overall risk score (Vyas et al., 2020, p. 874). This largely unjustified addition can direct care away from black patients as they will be perceived as lower risk than white counterparts presenting the same symptoms. This algorithm tries to distribute limited hospital resources in order to do the most good, a utilitarianism framework. This is a crucial decision that must be made at the macro level, potentially in conflict with the typical deontological – the idea that causing harm/neglect is never justified – framework common in doctor-patient interactions (Mandal et al., 2016, p. 6). This is an important and unavoidable problem in a world with limited resources, especially at majority black hospitals which historically are under-resourced and understaffed (Himmelstein et al., 2023, p. 586). The problem in these algorithms arise with the biased race adjustment factor, which is merely an extension of human bias drawn from the algorithm's creators. This can result in misappropriation of resources, away from those at equal or greater risk, as a result of the patient's race. When these algorithms are biased against specific racial groups, they no longer serve the utilitarian ethics they were designed to by redirecting resources away from where they could do the most good.

Another major factor is unique to the powerful deep learning neural networks that have become synonymous with AI. These algorithms are trained off of large datasets in the hopes they

will be able to generalize to new data. However, what can often happen is the algorithm can become overtrained to the training set. This becomes especially problematic when the training set does not reflect the diversity that would come through a hospital's cardiac wing. This can result in algorithms biasing towards their training set, which is all too commonly derived mostly from white medical data (Panch et al., 2019).

These deep learning neural networks algorithms are often used as diagnostic assists. These algorithms reflect the deontological framework, trying to assist doctors in identifying a problem in a specific patient so they can render the care they need. They don't factor in urgency or risk factor for comparison to other patients, instead they are designed to identify a problem and, in some cases, recommend the treatment best suited for a particular patient. However, when these algorithms fail as a result of bias, leading to a misdiagnosis disproportionately for minorities, this prevents them from getting the care they need, thus running counter to the very deontological framework they were designed to assist. Proper healthcare is a balance between utilitarian resource distribution, and deontological patient care, and AI tools can, in theory, improve decision making and eliminate human bias in both categories, but they must be intentionally designed to avoid machine bias.

The main question here is: what steps must be taken to mitigate the effects of racial bias in the cardiovascular health field? The intention is to build upon a plethora of past works on this subject as it is fairly well studied. Several of these papers have been cited in this prospectus. The final goal of this paper is to explore the current landscape of human and algorithmic biases, and propose potential solutions, compiled across multiple sources, in order to improve minority patient outcomes.

Technical Topic: During surgeries such as an open heart surgery, the heart must be stopped in order to allow for operation. Thus, the job of the heart, and the lungs, is taken over by a cardiopulmonary bypass machine. This machine oxygenates and circulates the blood via an external circuit. However, when blood is removed from the body it begins to clot. This is due in large part to factors released during tissue injury, and contact with an artificial surface in the tube walls (Levy, 2013, p. 589). If left unchecked, clots would form during the surgery, either killing the patient outright if the clotting is extensive enough, or causing postoperative complications such as a stroke if the clots travel to the brain.

Thus, it is essential that an anticoagulant is used to prevent clotting. Heparin is the standard due to its fast acting effect. Heparin binds to a protein called antithrombin-III (AT3), increasing its activity 1000 times. AT3 binds to thrombin, the key component of the clotting cascade, and prevents its activity (Hirsh et al., 2001, p. 1094). Typically, a bolus (large injection all at once) of heparin is administered prior to surgery in a dose calculated based on body weight. The effect is monitored by a device such as the Hemochron, which measures activated clotting time (ACT). This is a measure of the time it takes for a small sample of blood to clot after the introduction of a clotting catalyst, and it's usually kept above 480 seconds during surgery (Hoffmann et al., 2023, p. 286).

The combination of a roughly six minute testing time, and the manual operation of the device by the anaesthesiologist, means measurements are taken around every 30 minutes. This means any further heparin administration is also given in bolus. As a result of this dosing strategy heparin concentration peaks and then decreases until the next bolus, meaning it is possible to exceed the minimum heparin dose required for anticoagulant effectiveness. Furthermore, some studies have shown a correlation between the total heparin dosage and

severity of postoperative bleeding, despite heparin neutralization post surgery (Shuhaibar et al., 2004, p. 947). Postoperative bleeding is a frequent problem with this procedure, consuming up to 25 percent of blood products used by hospitals (Woodman & Harker, 1990, p. 1680). Reducing the occurrence or severity will greatly benefit not only hospitals, but also patient recovery and the cost burden.

We propose that continuous heparin infusion would allow for greater control of heparin levels, allowing for minimal dosing. However, with the current monitoring devices this would be largely impossible to implement, as they are only able to take a measurement at a maximum sampling rate of every six minutes. This would also require frequent and tedious work by the anaesthesiologist, potentially distracting them from other workflows. Thus we propose a novel device which is able to continuously monitor clot progression in a nonintrusive and non sample consumptive way.

While the method is yet to be finalized, one promising method we are considering is particle image velocimetry. This technique uses a strobe laser and a digital camera to track the movement of particles in fluid in order to determine the velocity and flow profiles. In our case, this could be accomplished by tracking red blood cells themselves (Pitts & Fenech, 2013). We could then relate the velocity or the flow profile of the fluid to clot progression based on experimentation.

The end goal is to make a prototype for a device which is able to output heparin dosing adjustments based on its measurements completely autonomously. This would open the door for a future goal where this device is then combined with a heparin pump system to control dosing, similar to an insulin pump, but that is likely out of the scope of this project.

Conclusion: In summary, the goal of this project is both material and immaterial improvements in the cardiac healthcare field. For the STS portion, the intent is to propose a myriad of solutions, based on research, to reduce the effect of bias in cardiac health, through both human and algorithmic interventions. The hope is that some of these solutions will be able to enact equitable treatment opportunities, thereby improving cardiac outcomes for minorities. On the technical side, the intent is to develop a novel device which is capable of continuously monitoring clot progression during cardiopulmonary bypass. This device will allow for minimal heparin dosing, which in turn should decrease rate and severity of postoperative bleeding, thus improving patient outcome. All in all, the hope is to make a meaningful contribution to the cardiac field and improve outcomes for all patients.

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