Original Research

Smartphone Detection of Fetal Movements Using Artificial Intelligence

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OBJECTIVE: To evaluate whether machine learning could be used with audio recordings from a smartphone to detect fetal movements that create disruptions of the amniotic fluid environment.

METHODS: We conducted a prospective study to simultaneously record fetal movements seen on ultrasound and audio recordings using a smartphone placed on the maternal abdomen and to compare these with maternal perception of fetal movements. Smartphone audio segments were preprocessed to reduce noise, window the signal, and divide them into typed 1-second audio snippets. These were subsequently converted into visual representations of their acoustic features known as Mel-frequency cepstral coefficients (MFCCs). Selected MFCCs were examined to evaluate how feature characteristics vary with gestational age and body mass index (BMI). Fetal movement detected on ultrasonography was considered the gold standard to estimate the accuracy of model prediction applied to tagged audio segments and maternal perception of movement. The area under the receiver operating characteristic curve (AUROC) was used to evaluate the accuracy of the binary classifier to detect the presence or absence of any fetal movement. Macro F1 scores were used to evaluate the accuracy of more refined movements (gross movement, breathing, and hiccups). Isolated trunk and limb movements were marked with a single timestamp, and continuous or repetitive gross fetal movements were annotated with a continuous timestamp spanning the duration of the activity.

RESULTS: Overall, 136 participants were included; 30 patients were followed longitudinally, and 106 received only one study visit. Generalized additive models were applied to selected MFCCs and analyzed separately for cohort recordings and fetal movement types. Results revealed nonlinear associations with gestational age (adjusted $P<.001$) and maternal BMI (adjusted $P<.001$), informing algorithm refinement. In our final model adjusting for gestational age and maternal BMI, detection of fetal movement with smartphone audio recordings was noted to be highly accurate. Binary detection of the presence or absence of any fetal movement was clinically significant (AUROC 0.886, 95% CI, 0.883–0.888) compared with maternal perception of 3.0%. Gross fetal movement was detected at an accuracy of 64.0% (95% CI, 63.1–66.7%), whereas maternal perception of fetal movements yielded an accuracy of 18.0%. Similarly, the accuracy of audio recordings compared with ultrasound-detected fetal breathing movements was found to be 93.0% (95% CI, 92.0–94.2%) as compared with 3.0% for maternal perception. Finally, the accuracy of audio recordings for fetal hiccups was 73.0% (95% CI, 68.2–76.2%) compared with 32.0% for maternal perception.

CONCLUSION: Audio-based assessment of fetal movement using a smartphone can reliably detect gross fetal movements, as well as fetal breathing and hiccups observed on ultrasonography, and proved superior to maternal perception of movements.

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Fetal death after 28 weeks of gestation is defined as *late stillbirth*. Using this definition, the United Nations Children's Fund (UNICEF) has determined that more than 1.9 million stillbirths occurred worldwide in 2023; most of these deaths occurred in low- and middle-income countries.[1] In the United States in 2023, the rate of late stillbirth was reported to be 2.80 per 1,000 births.[2]

Current gold-standard strategies for preventing late stillbirth are limited to the use of in-clinic ultrasonography with or without fetal heart rate monitoring in patients with pregnancies identified as high risk, an approach that can be cost prohibitive and burdensome for the patient. Cost estimates of in-clinic antenatal testing suggest a range of $57,300 to $1,719,000 to prevent one stillbirth.[3] This approach also fails to address stillbirths that occur in uncomplicated pregnancies.

Maternal perception of decreased fetal movements has long been studied as a predictor of stillbirth.[4] A meta-analysis of 39 nonrandomized studies found that maternal perception of decreased fetal movements was associated with an odds ratio (OR) of 3.44 (95% CI, 2.02–5.88) for subsequent stillbirth.[5] Several online apps are available to assist patients in quantitating maternal-perceived fetal movements. However, they have not been clinically validated, and whether they are an effective method of antenatal surveillance remains unclear. We therefore aimed to determine whether fetal movements could be reliably detected from smartphone audio recordings using machine learning and to assess how maternal body mass index (BMI, calculated as weight in kilograms divided by height in meters squared) and gestational age influence acoustic features. We also examined whether more refined characterization of fetal movements (gross movements, fetal breathing, and hiccups) could similarly be detected using this technology.

METHODS

Pregnant women were recruited by research nurses in local community-based obstetric practices and inner-city prenatal clinics. Participants were recruited both in person and with flyers containing a QR code posted in prenatal clinics. Inclusion criteria included being an English- or Spanish-speaking woman between 18 and 45 years of age with a singleton pregnancy dated by first-trimester ultrasonography, gestational age of 24–38 6/7 weeks, absence of maternal medical complications, and no evidence of abnormal fetal growth or congenital anomalies. All participants signed written informed consent; the study was approved by the IRB of the University of Texas at Austin (IRB #00001552).

This was a prospective study that included both longitudinal and cross-sectional cohorts to address complementary analytic objectives. The longitudinal cohort enabled assessment of within-individual changes in fetal acoustic features across gestation, and the cross-sectional cohort broadened representation across maternal body habitus and gestational ages, thereby enhancing generalizability.

Serial 30-minute recordings were obtained in both the longitudinal and cross-sectional study cohorts between 24 and 38 weeks of gestation. Longitudinal cohort patients were seen on multiple occasions with advancing gestation; recordings were obtained from the cross-sectional cohort patients on a single occasion in the same gestational age window. Longitudinal cohort patients were not provided with any feedback between sessions related to their perceptions of fetal movement. Gestational age, maternal BMI, abdominal wall thickness, placental location, amniotic fluid index, and parity measures were collected at each visit. All study visits were conducted in one of two ultrasound rooms in relatively quiet ambient conditions. With the patient in a supine position, a smartphone (iPhone 10.0) was oriented vertically on the patient's abdomen (Fig. 1) in a paramedian location at the miduterus level, held in position with a custom apparatus. A simultaneous, continuous real-time ultrasonogram was performed (General Electric E10 or E22), with the image oriented to the sagittal plane of

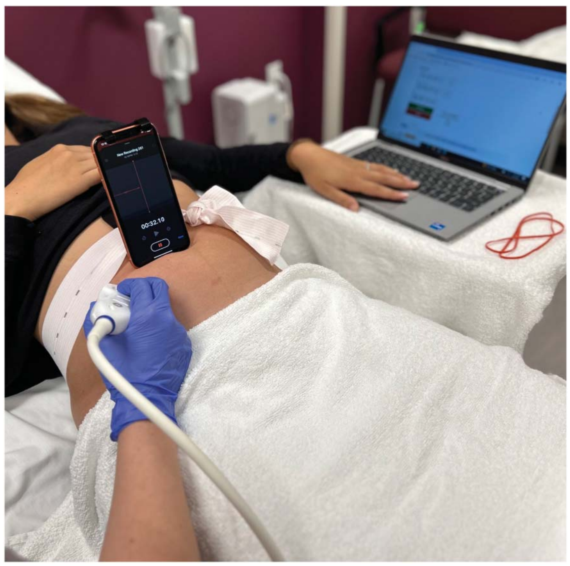

Fig. 1. Co-registration of data collection from ultrasonography, smartphone audio, and patient-perceived fetal movement.

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the fetus to visualize the entire trunk. The patient was asked to simultaneously record their perception of fetal movements by depressing a key on a laptop computer with a co-registered timer synchronized to the audio and video recordings. Ten additional 15-minute recordings were undertaken in which the patient held the smartphone in place to validate a real-world audio recording method (Fig. 2). These “hand-held” recordings were analyzed to assess concordance with the other study-protocol recordings.

Two experienced ultrasonographers reviewed all video recordings offline and used timed software to indicate fetal movement events that coincided with the video timer. All ultrasound recordings were downloaded to an encrypted storage device. Patient demographic data, maternal perception files, and ultrasonographer review files were securely stored in a REDCap database. Isolated trunk and limb movements were marked with a single timestamp; continuous or repetitive gross fetal movements were annotated with a continuous timestamp spanning the duration of the activity.

A second ultrasonographer, using the same procedure and software, consistently reviewed the video recordings to annotate fetal breathing and hiccups. *Fetal breathing* was defined as rhythmic diaphragmatic, chest, or abdominal motion and annotated with timestamps marking onset and continuation until cessation.

Fig. 2. Orientation of smartphone and ultrasound transducer on maternal abdomen for simultaneous recording.
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To control for artifacts, we preprocessed audio recordings by 1) windowing acoustic signals with a fast Fourier transform length of 2048, allowing us to identify subtle, low-frequency changes; 2) creating uniform 1-second segments with labels for specific fetal movements based on ultrasound annotations denoting quality of movement types (breathing and hiccups took first precedence followed by gross movements); and 3) converting audio into numerical representations of acoustic features known as Mel-frequency cepstral coefficients (MFCCs, Fig. 3).[6] Commonly used in audio classification, MFCCs compactly summarize the spectral shape of a sound, capturing characteristics that distinguish different noises while being relatively insensitive to changes in pitch, volume, and background noise. We extracted 39 MFCC-related features per 1-second segment, encompassing static coefficients and their temporal derivatives to ascertain both spectral structure and short-term dynamics.

Each 1-second segment initially generated 39 time-varying values per MFCC feature (39 frames per coefficient), totaling 1,521 values per segment. To reduce dimensionality while retaining key acoustic information, we applied principal component analysis to the time-frame values within each MFCC separately. The first principal component for each MFCC, identifying at least 95% of its within-feature variance, was retained as a single summary value, resulting in 39 compressed MFCC values per 1-second segment. Next, to reduce redundancy and avoid overfitting, we evaluated the compressed MFCCs for correlation and multicollinearity within each type of fetal movement (breathing, gross movements, and hiccups) and cohort (longitudinal or cross-sectional). To prevent model overfitting, we selected a Pearson correlation threshold of $r > 0.7$. This retains physiologically informative features while eliminating redundant acoustic information–a critical step, given the known spectral overlap among MFCCs. In parallel, we excluded features with a variance inflation factor of 5 or higher to further guard against unstable parameter estimates. This procedure was performed separately for longitudinal and cross-sectional datasets to account for repeated measurements in the longitudinal data.

We assessed whether reduced acoustic features varied systematically with gestational age and maternal BMI to determine whether our model should

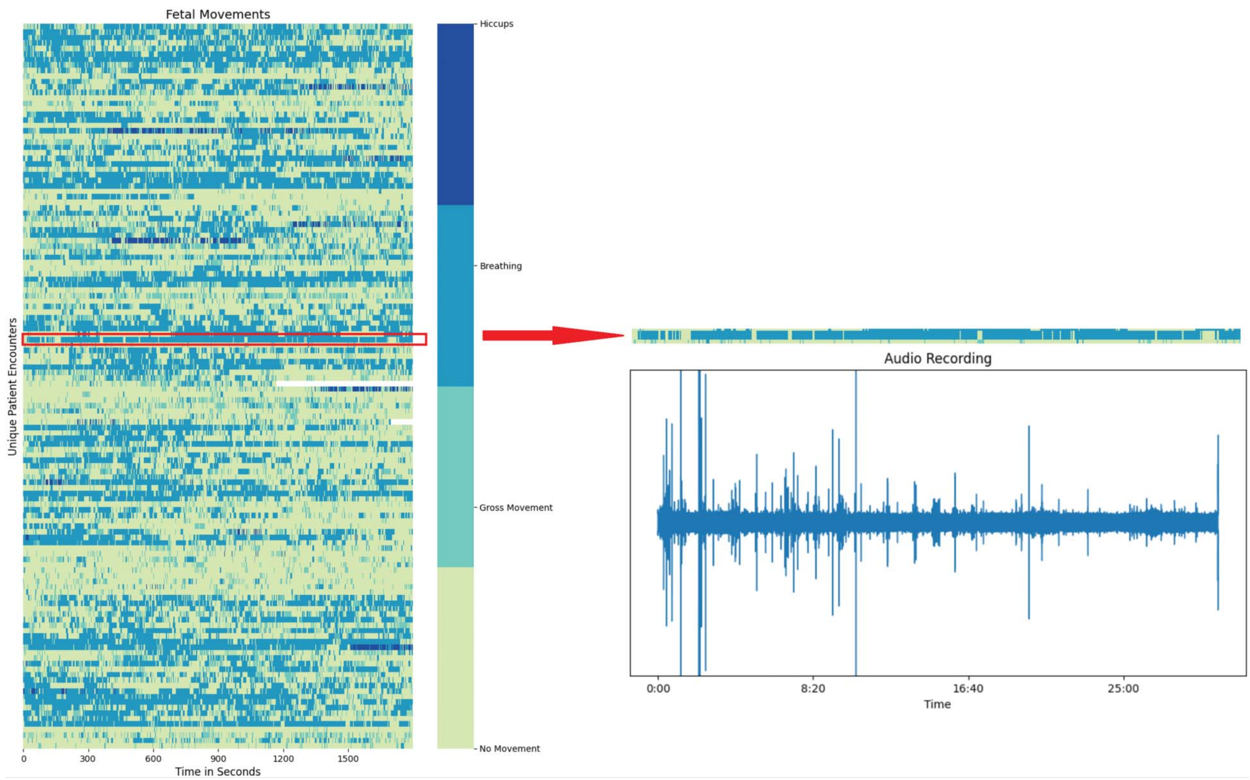

Fig. 3. Heat map of fetal movements noted on ultrasonography. Each *horizontal row* represents a patient. *Color key* to the right of heat map indicates the color for each of four categories: hiccups, breathing, gross movements, and no movement. Excerpt of single patient indicates significant breathing activity on the audio tracing.

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account for these factors. Gestational age was selected because of known differences in fetal size, anticipated differences in movement patterns, and tissue properties affecting sound generation and transmission. Maternal BMI was examined because body habitus can influence acoustic attenuation and signal quality. Both variables are routinely available in obstetric care, enabling calibration of algorithms using widely accessible information. Additional clinical characteristics including placental location, abdominal wall thickness, amniotic fluid index, and parity accounted for less than 1% of acoustic variance and were not included in model adjustments.

For each dataset (2 cohorts×3 fetal movement types), relationships between individual MFCC features and gestational age or BMI were visualized with scatterplots and smooth curves to assess linearity. Observing evidence of nonlinear associations, we fitted generalized additive models with cubic splines for each MFCC feature, treating gestational age or BMI as continuous predictors using the mgcv package in R 4.4.1. We used estimated degrees of freedom (edf) to characterize association shapes (edf>1 indicates nonlinearity). Features were evaluated independently, with *P* values adjusted for multiple comparisons using the false discovery rate.

We used area under the receiver operating characteristic curve (AUROC) to evaluate model accuracy in distinguishing the binary choice of fetal movement compared with no movement from audio tagged according to ground truth ultrasonography. Model accuracy for detecting multiclassification, further distinguishing gross movement, breathing and hiccups, was evaluated using macro F1 scores, which balance precision and recall with accuracy. The bootstrap CI (Boot) method was used to compute CIs for all model predictions (Table 1). A z-proportion test was used to calculate statistical significance between patient-perceived movements and model predictions. Additionally, Pearson's correlation with CIs were calculated to compare hand-held audio to device-held audio.

An automated ensemble pipeline was developed to classify fetal movements indicated on abdominal audio recordings. The baseline model used scikit-learn gradient-boosted decision trees (a supervised

Table 1. Comparison of Ultrasound-Detected Fetal Movements With Maternal Perception and Smartphone Audio Recording–Generated Artificial Intelligence Models

Type of Fetal Movement on Ultrasonography	Patient-Perceived Accuracy of Observed Fetal Movement (%)	Audio Recording AI Accuracy			
		Model 1*	*P*	Model 2†	*P*
Gross movement	18.0	56.0 (55.8–57.2)	<.001	64.0 (63.1–66.7)	<.001
Breathing	3.0	90.0 (89.9–91.3)	<.001	93.0 (92.4–94.2)	<.001
Hiccups	32.0	68.0 (64.5–69.9)	<.001	73.0 (68.2–76.2)	<.001

AI, artificial intelligence.
Data are macro F1 score (%) (95% CI) unless otherwise specified.
* Model 1 compared fetal movements detected by audio-recording AI with those detected by patient perception.
† Model 2 compared fetal movements detected by audio-recording AI with those detected by patient perception, adjusting for maternal body mass index (BMI) and gestational age at time of measurement.

machine learning algorithm tolerant of scale and imbalance) trained on ultrasonographer annotations and evaluated using a leave-one-participant-out protocol to ensure generalizability to naïve sessions. Accuracy for the binary classifier was measured using AUROC scores (initially to detect the presence of any fetal movement), and accuracy for the multi-classifier was measured using macro F1 scores. Model hyper parameters were refined using the scikit-learn hyperopt library to account for nonlinear relationships between acoustic features and fetal movement type, class imbalance, and relevant clinical factors identified in feature analysis. Ensemble models, including random forest, support vector machines, and gradient-boosted trees, were trained on MFCC features, with tuned weighting to minimize false positives.

RESULTS

Overall, 136 patients agreed to participate in the study. The longitudinal study population consisted of 30 patients who completed a total of 131 recording sessions. Eighteen patients completed five recording sessions, seven completed four sessions, three completed three sessions, and two completed two sessions (a total of 3,930 minutes of recordings). The average age of participants was 32.6 years (SD 3.9 years; range 24.0–41.0 years), with a median gravidity of two (range 1–6) and a median parity of one (range 0–3). The average BMI across participants and all visits was 28.61 (SD 4.01; range 20.09–36.64). A majority of participants self-reported their race as White (26/30) and their ethnicity as non-Hispanic (21/30). One patient who was initially enrolled was excluded because she was not within the appropriate gestational age range window.

The cross-sectional portion of the study population consisted of 106 patients (a total of 3,180 minutes of recordings). The average age of participants was 32.7 years (SD 4.8 years; range 22.0–46.0 years), with a median gravidity of two (range 1–9) and a median parity of zero (range 0–3). Across participants, average BMI was 28.75 (SD 4.03; range 21.64–43.37). A majority of participants self-reported their race as White (89/106) and their ethnicity as non-Hispanic (82/106).

After filtering to remove redundant MFCCs, each dataset retained four to nine coefficients, varying by fetal movement type and cohort. Two coefficients (M24, M36), representing fine frequency details, were consistent across all movement types and cohorts, identifying core acoustic patterns. Additional coefficients were shared across most movement types, reflecting detailed spectral "texture," but lower-order coefficients (M2–M4) were less consistent and mostly associated with breathing or hiccups.

Gestational age ranged from 24 to 38 weeks in both cohorts (Fig. 4). Across groups, gestational age was significantly associated with multiple MFCCs for all types of fetal movements (all adjusted $P<.001$), with edf values near 9, indicating highly nonlinear relationships across gestation. This nonlinear pattern suggests that the acoustic features of fetal movements change in complex ways rather than linearly as gestation progresses. Maternal BMI was significantly associated with MFCC-derived acoustic features across both longitudinal and cross-sectional cohorts (all adjusted $P<.001$), with strongly nonlinear relationships observed across BMI values (edf $\approx$ 9).

Using our ensemble model described previously, we computed model predictions to distinguish the presence of any fetal movement from no movement, as well as model predictions to capture fetal movements with greater fidelity. We also computed models without (model 1) and with (model 2) the inclusion of gestational age and BMI. Model 1 achieved an AUROC score of 0.874 (95% CI, 0.872–0.876), and model 2 achieved an AUROC score of 0.886 (95%

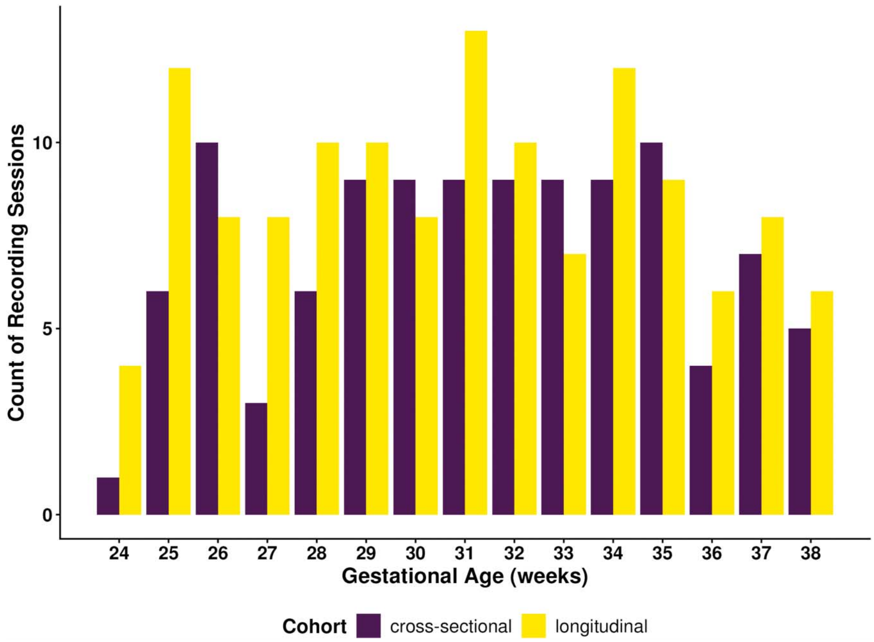

Fig. 4. Histogram of gestational age across visits.

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CI, 0.883–0.888). It is relevant to note that patients perceived just 3.0% of any fetal movement.

Our multiclassifier was computed for model 1 and model 2 to characterize fetal movement type, allowing us to examine accuracy for detecting refined movements. Model 1 proved inferior to model 2 for all predictions. Gross movement was correctly detected in 56.0% (95% CI, 55.8–57.2%) of cases using model 1 compared with 64.0% using model 2 (95% CI, 63.1–66.7%), breathing was correctly classified in 90.0% of cases (95% CI, 89.9–91.3%) compared with 93.0% (95% CI, 92.4–94.2%) and hiccups were correctly classified in 68.0% of cases (95% CI, 64.5–69.9%) compared with 73.0% (95% CI, 68.2–76.2%; Table 1). Audio-based detection of fetal movements in both models demonstrated substantially higher agreement with ultrasound-confirmed events compared with maternal perception across all fetal movement types. For gross fetal movements, model 1 (excluding gestational age and BMI) achieved 56.0% accuracy and model 2 (including gestational age and BMI) had an accuracy of 64.0% compared with 18.0% for maternal perception, representing a 3.5-fold improvement ($P<.001$).

For fetal breathing movements, model 1 correctly classified breathing 90.0% of the time and model 2 93.0% in ultrasound-confirmed events, whereas maternal perception detected only 3.0% of events, corresponding to a 30-fold improvement ($P<.001$). For fetal hiccups, which are more readily perceived by patients, model 1 achieved 65.0% accuracy and model 2 achieved 68.0% accuracy compared with 32.0% for maternal perception, a twofold improvement ($P<.001$).

All 10 of the 15-minute hand-held recordings detected gross movement, eight detected breathing, and none detected hiccups. Gross movements had an average correlation of 98.6% (95% CI, 97.2–99.1%), and breathing had an average correlation of 98.3% (95% CI, 97.5–98.6%), indicating a high degree of similarity between the hand-held and device-held recording conditions for both fetal movement types.

DISCUSSION

We have demonstrated that audio recordings from a smartphone held against the abdominal wall of the pregnant patient can more accurately detect fetal movements when compared with maternal perception. By analyzing hundreds of thousands of recording segments, we identified a set of consistent and unique acoustic features that reliably distinguished different fetal movement types. Although absolute acoustic feature values varied across cohorts, consistent relative patterns by fetal movement type were preserved, reflecting expected physiologic and recording-context differences rather than instability in model behavior.

More than five decades ago, Sadovsky and Yafee[7] reported seven cases of decreased daily fetal movements in association with fetal compromise and fetal death. Since that time, several cohort and randomized studies have supported fetal movement tracking as a possible intervention to help prevent stillbirth.

Heazell et al[4] interviewed 291 women with late stillbirths and 733 women in a control group to characterize maternal perception of fetal movements during the 2 weeks before delivery. One episode of decreased fetal movements was associated with a risk for stillbirth (OR 2.36, 95% CI, 1.69–3.30), and three or more episodes were associated with an increased risk (OR 5.11, CI, 3.22–8.10). Several case-cohort studies using fetal movement counting have reported an overall relative risk of 0.42–0.76 for stillbirth and a relative risk of 0.24–0.56 for avoidable stillbirths.[8,9] Neldam et al[10] published a randomized trial of 2,250 pregnant women that included a fetal movement counting intervention, reporting an overall relative risk of 0.25 for stillbirth and a relative risk of 0.27 for avoidable stillbirths.

There are several challenges in using the maternal perception of fetal movements as a predictor for stillbirth. Pregnant women do not perceive all fetal movements seen on simultaneous ultrasonography. In one study, maternal perception of fetal movements coincided with ultrasound-detected movements in only 33% of cases.[11] This is similar to the findings of the current study, in which pregnant women perceived only 3% of all fetal movements combined, and 18% of gross fetal movements seen on simultaneous ultrasonography. In addition, fetal movements such as breathing, a reassuring sign of fetal well-being, are even less likely to be perceived by pregnant patients. Pregnant women in the current study perceived only 3% of fetal breathing episodes noted on ultrasonography.

The most recent guidelines from the American College of Obstetricians & Gynecologists (ACOG) and the Society for Maternal-Fetal Medicine (SMFM) propose that antenatal surveillance be initiated once or twice weekly at 32 weeks of gestation or starting 1–2 weeks before the gestational age at which a previous stillbirth occurred.[12] Such testing involves the use of ultrasonography (biophysical profile), fetal monitoring (nonstress test), or a combination of both (modified biophysical profile), performed once or twice weekly in an outpatient setting. These visits involve a significant time and financial burden for the patient. Additionally, both ACOG and SMFM have published guidelines for antenatal surveillance for more than 25 other fetal or maternal conditions associated with a relative risk for stillbirth of 2.0 or greater on the basis of retrospective studies.[13] Unfortunately, these recommendations are not based on evidence from randomized clinical trials, nor have they been subjected to a cost-analysis evaluation. In fact, in one study of almost 2,000 pregnancies in which antenatal testing was employed for high-risk conditions, the stillbirth rate remained at 7.7 per 1,000 births.[14] These testing methods also do not account for a change in fetal status between visits, nor do they have the ability to assess changes in fetal status over time.

We demonstrated that a novel acoustic recording method can detect fetal movements with an accuracy approaching that of trained ultrasound technicians and far exceeding maternal perception alone. These findings support the clinical potential of passive audio monitoring as an adjunct to ultrasound-based assessment, particularly in settings where access to imaging is limited. Importantly, our results suggest that the acoustic characteristics of fetal movement change in nonuniform ways across gestation, reflecting underlying physiologic maturation of the fetus and evolving maternal–fetal anatomy. In addition, maternal body habitus was shown to influence acoustic signal properties, underscoring the importance of considering maternal physiology when interpreting fetal movement recordings.

The current study advances the growing call and effort to translate machine learning and artificial intelligence into actionable tools for obstetric care.[15,16] By leveraging built-in smartphone microphones to obtain recordings, our approach minimizes operator dependency, reduces patient costs, and provides a proof of concept for a scalable and accessible method for home-based fetal monitoring. As algorithmic medicine continues to evolve, such tools have the potential to democratize fetal surveillance; enable earlier detection of decreased movement patterns associated with stillbirth risk; and ultimately promote more equitable, data-driven prenatal care.

Limitations of the current study include the lack of racial and ethnic diversity of the study population. All measurements were recorded with the patient in a supine position in a relatively quiet room. Thus, it remains unknown how the audio measurements would perform in other settings. In addition, the study was conducted using an iPhone 10.0; the sensitivity of the audio recordings may be different with other iPhone versions or Android-based phones. Future studies will be needed to assess the accuracy of fetal movement detection using other smartphone platforms.

In conclusion, audio-based assessment of fetal movements using a smartphone can reliably detect gross fetal movements, as well as fetal breathing and hiccups. Prospective clinical trials in a large patient population will be necessary to see whether this approach can lead to a reduction in stillbirth.

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