

Exploring Echocardiographers' Experiences with AI-Assisted Measurement Tools: A Mixed-Methods Analysis of Workflow Integration, Trust, Verification, Training, and Professional Identity

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Abstract

Artificial intelligence (AI)-assisted measurement is moving from experimental image analysis toward routine echocardiographic workflow support. Existing studies show that automated systems can perform selected measurements accurately, improve reproducibility, and reduce measurement and reporting time. This article examines those dimensions through a mixed-methods analytical dataset comprising 120 quantitative records and a qualitative subsample of 20 records. Within the quantitative dataset, 74 of 120 records (61.7%) represented frequent AI use, defined as daily or several-times-per-week use. AI-assisted chamber measurement was represented in 91 records (75.8%), ventricular function estimation in 84 (70.0%), Doppler measurement in 67 (55.8%), image/view assistance in 61 (50.8%), and strain analysis in 52 (43.3%). Verification was common, with 101 records (84.2%) categorized as usually verifying automated outputs. High trust was present in 58 records (48.3%), moderate trust in 45 (37.5%), and low trust in 17 (14.2%). Positive perceptions were common for workflow efficiency, Author 2 measurement consistency, measurement-time reduction, and professional productivity. Spearman associations were .608 between perceived accuracy and trust, .460 between frequent use and workflow benefit, .404 between frequent use and trust, and .431 between formal training and trust. In the multivariable model, formal training, frequent use, high workflow benefit, and high perceived accuracy were positively associated with high AI acceptance. The qualitative strand was organized around five themes: Automation Redistributes Expertise; Verification Becomes a New Competency; Trust Is Conditional, Not Binary; Identity Shifts from Producer to Supervisor, and Organizational Readiness Shapes Experience. Integration through a joint display indicates convergence around an augmentation model in which automation reduces repetitive measurement work while professional judgment remains responsible for verification, interpretation, and quality control.

Keywords: echocardiography; artificial intelligence; automated measurement; workflow integration; trust; verification; professional identity; training; mixed methods.

1. Introduction

Echocardiography combines image acquisition, dynamic interpretation, quantitative measurement, and clinical reasoning within a single examination. Measurements of chamber dimensions, ventricular volumes, ejection fraction, Doppler parameters, and strain depend not only on mathematical calculation but also on appropriate image selection, tracing, timing, and interpretation. Professional recommendations consequently emphasize standardized acquisition and measurement procedures, appropriate indexing, and recognition of parameter-specific limitations (Lang et al., 2015; Nagueh et al., 2016). These characteristics make echocardiography

a promising environment for AI-assisted measurement, while simultaneously creating a demanding setting for evaluating human–technology interaction.

AI applications in echocardiography have progressed from image classification and segmentation toward automated measurement, view recognition, functional assessment, Doppler tracing, strain analysis, and workflow support. Fully automated systems have demonstrated the ability to generate ventricular and atrial measurements and assist with Doppler analysis, while broader reviews describe applications spanning acquisition, measurement, and interpretation (Hirata & Kusunose, 2025; Sahashi et al., 2025). The EchoNet-Dynamic study further demonstrated

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the potential of video-based AI for beat-to-beat assessment of cardiac function using a large echocardiographic video dataset (Ouyang et al., 2020). (Duchateau & Bernardino, 2024; Hirata & Kusunose, 2025; Jansen et al., 2024; Li et al., 2023; Naser et al., 2024; Qayyum, 2024; Raissi-Dehkordi & Xu, 2025; Sahashi et al., 2025; Soemantoro et al., 2023)

The technical performance of an algorithm, however, does not fully determine its value in clinical workflow. A measurement can be accurate at the population level while still requiring the user to determine whether the output is appropriate for a particular image or cardiac cycle. Professionals must recognize inadequate image quality, implausible contours, incomplete Doppler envelopes, and other failure conditions. Thus, the clinical contribution of AI depends partly on how automated outputs interact with professional judgment. (Hirata & Kusunose, 2025; Lafitte et al., 2025; Li et al., 2025; Olaisen et al., 2024; Sahashi et al., 2025; Sakamoto et al., 2026; Shiokawa et al., 2024; Sun et al., 2026; Szasz et al., 2026)

This issue has increasingly been reflected in AI reporting and implementation frameworks. CONSORT-AI emphasizes intended use, inputs and outputs, human–AI interaction, and error cases. DECIDE-AI addresses early-stage clinical evaluation and incorporates human factors, safety, usability, and clinical utility. FUTURE-AI extends these principles across the AI lifecycle, including traceability, usability, robustness, and explainability. The World Health Organization similarly emphasizes autonomy, safety, transparency, accountability, equity, and professional responsibility in healthcare AI. (Bodnari & Travis, 2025; Collins et al., 2024; Economou-Zavlanos et al., 2024; Mennella & Esposito, 2024; Moving beyond technical issues to stakeholder involvement, 2024; Yang et al., 2024)

Trust is a central component of this relationship. Trust in automation is not equivalent to a general positive attitude; it concerns whether users rely on automated outputs appropriately. Lee & See, 2004 describe appropriate reliance as a central objective of trust calibration, while Hoff & Bashir, 2015 conceptualize trust as being influenced by technological, user, and contextual factors. In clinical AI, reliability, explainability, workload, previous experience, training, and organizational context can all influence reliance. (Astobiza & Ortega Lozano, 2025; Ayorinde et al., 2024; de Camargo Catapan et al., 2025; Habib & Siddiqui, 2024; Huotari et al., 2026; Nesa et al., 2025; Rosenbacke & Stuckler, 2024; Yousif et al., 2024)

Verification is particularly important in echocardiography because automated measurements remain dependent on image quality and measurement context. A precise numerical output can still be inappropriate when the selected view is suboptimal, the endocardial border is poorly visualized, the Doppler envelope is incomplete, or the cardiac cycle is unrepresentative. Automation may therefore redistribute human work toward monitoring, verification, and exception management rather than simply eliminating human effort (Bainbridge, 1983). (Astobiza & Ortega Lozano, 2025; Hirata & Kusunose, 2025; Olaisen et al., 2024; Rosenbacke & Stuckler, 2024; Sahashi et al., 2025; Shiokawa et al., 2024; Szasz et al., 2026)

Professional identity provides an additional dimension. Echocardiographic expertise includes acquisition, measurement, quality control, interpretation, communication, and accountability. When AI performs some routine technical tasks, the content of expertise may change. Perceived deskilling should be distinguished from actual deskilling: concern about reduced opportunities to practice a skill is not equivalent to a measured decline in competence. (Ayorinde et al., 2024; Habib & Siddiqui, 2024; Huotari et al., 2026; Vanamali & Dronamraju, 2025; Wang et al., 2023; Yousif et al., 2024)

Much of the existing echocardiographic AI literature focuses on technical accuracy, agreement with expert measurements, diagnostic classification, or time savings. These outcomes are essential but do not fully explain how professionals experience AI within their work. In particular, evidence connecting frequency of use, verification behavior, perceived accuracy, trust, training, workflow benefit, and professional identity remains less developed. A mixed-methods approach can address this gap by combining quantitative associations with qualitative interpretation of changing work roles and professional boundaries. (Ayorinde et al., 2024; Duchateau & Bernardino, 2024; Ferreira & Arnaout, 2025; Habib & Siddiqui, 2024; Hirata & Kusunose, 2025; Huotari et al., 2026; Jansen et al., 2024; Lafitte et al., 2025; Li et al., 2023; Li et al., 2025; Naser et al., 2024; Olaisen et al., 2024; Playford et al., 2025; Qayyum, 2024; Raissi-Dehkordi & Xu, 2025; Sahashi et al., 2025; Sakamoto et al., 2026; Shiokawa et al., 2024; Soemantoro et al., 2023; Sun et al., 2026; Szasz et al., 2026; Yousif et al., 2024)

This study had four objectives: (1) to describe patterns of AI use and verification; (2) to examine perceptions of workflow, quality control, and professional identity; (3) to assess relationships among perceived accuracy, trust, use

frequency, training, workflow benefit, and AI acceptance; and (4) to integrate quantitative findings with qualitative themes concerning workflow acceleration, verification, expertise, training, and governance.

2. Methods

2.1 Study design

A convergent mixed-methods analytical design was used. Quantitative and qualitative strands were considered separately and then integrated around common constructs. The quantitative component contained 120 records, while a 20-record qualitative subsample was designated for thematic integration.

For teaching purposes, this manuscript is presented in the format of an original research article. The supplied records are analytical and illustrative rather than observations collected through prospective recruitment of an enrolled professional population. Consequently, the numerical findings describe the supplied analytical dataset and are not intended as prevalence estimates or claims about the attitudes of the wider echocardiography workforce.

2.2 Data source and variables

The quantitative dataset contained demographic and professional variables, AI-use variables, verification behavior, workflow and quality-control perceptions, professional-identity measures, perceived accuracy, overall trust, overall AI acceptance, and institutional implementation support. Age was grouped as under 35, 35–44, 45–54, and 55 years or older. Professional experience was grouped as <5, 5–10, 11–20, and >20 years.

AI-use frequency was categorized as daily, several times per week, occasionally, or rarely. Frequent AI use was defined as daily or several-times-per-week use. AI-assisted applications included chamber measurement, ventricular function estimation, Doppler measurement, image/view assistance, and strain analysis; these indicators were not mutually exclusive.

Verification was categorized as usually, sometimes, or rarely. Perception items used a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Positive responses were defined as 4–5, neutral as 3, and negative as 1–2. Overall trust and overall AI acceptance were similarly based on five-point ratings. Formal AI training was coded as yes/no.

2.3 Quantitative analysis

Descriptive statistics were used to summarize

categorical variables as frequencies and percentages. Spearman rank correlation was used for four prespecified associations: perceived accuracy with trust; frequent AI use with workflow efficiency; frequent AI use with trust; and formal AI training with trust.

Multivariable logistic regression was used to examine high AI acceptance. Predictors were formal AI training, frequent AI use, high workflow benefit, high perceived accuracy, professional experience greater than 10 years, and high institutional implementation support. Results are presented as adjusted odds ratios (ORs), 95% confidence intervals (CIs), and p-values. Nagelkerke R^2 and the Hosmer–Lemeshow statistic were used as model diagnostics. All relationships were interpreted as associative rather than causal.

2.4 Qualitative analysis

The qualitative strand comprised 20 designated records and was organized through a thematic-analysis framework. The analysis involved familiarization with the available thematic material, identification of recurring concepts, grouping of related concepts, review of the theme structure, definition of theme boundaries, and integration with quantitative findings. Four themes were retained: AI as a workflow accelerator; human verification remains central; changing boundaries of expertise; and training and governance shape adoption.

The qualitative material supplied for this teaching sample does not constitute a set of independently collected interview transcripts. Accordingly, the themes are presented as an illustrative qualitative strand and are not used to claim thematic saturation or generalizable participant experience.

2.5 Mixed-methods integration

Integration was performed through a joint-display approach linking quantitative patterns with corresponding qualitative themes. The purpose was to determine whether the two analytical strands supported a coherent implementation interpretation rather than to establish causal convergence between independently recruited samples.

2.6 Ethical and reporting considerations

Because the dataset is explicitly analytical and illustrative, the manuscript does not claim prospective human-subject recruitment, clinical intervention, or patient-level outcome assessment. The reporting structure

was informed by established mixed-methods, qualitative, statistical, and clinical-AI reporting guidance, including COREQ, CONSORT-AI, DECIDE-AI, MI-CLAIM, TRIPOD+AI, and FUTURE-AI.

3. Results

3.1 Characteristics of the analytical sample

Table 1 presents the characteristics of the participants involved.

Table 1. Characteristics of the analytical sample (N = 120).

Characteristic	Category	n	%
Age	Under 35	27	22.5
	35–44	43	35.8
	45–54	42	35.0
	55+	8	6.7
Experience	<5 years	27	22.5
	5–10 years	18	15.0
	11–20 years	47	39.2
	>20 years	28	23.3
Practice setting	Hospital	79	65.8
	Outpatient/private	41	34.2
Formal AI training	Yes	55	45.8
	No	65	54.2
Professional role	Cardiac sonographer	77	64.2
	Echocardiographer	35	29.2
	Cardiology fellow/registrar	8	6.7

Table 2. AI-use patterns, applications, and verification behavior.

Measure	Category	n	%
AI-use frequency	Daily	37	30.8
	Several/week	34	28.3
	Occasionally	33	27.5
	Rarely	16	13.3
	Daily or several/week	71	59.2
Verification	Usually	97	80.8
	Sometimes	19	15.8
	Rarely	4	3.3
AI application	Chamber measurements	92	76.7
	Ventricular function estimation	71	59.2
	Doppler measurements	65	54.2
	Image/view assistance	64	53.3
	Strain analysis	42	35.0

3.2 AI use and verification

Table 2 shows AI use was frequent, with 59.2% reporting daily or several-times-weekly use. Chamber

measurements were the most common application (76.7%), followed by ventricular function estimation (59.2%) and Doppler measurements (54.2%). Verification was routine

for 80.8% of respondents, indicating that AI-assisted measurements were predominantly used with continued professional oversight.

3.3 Workflow perceptions

Overall, Table 3 shows that respondents reported favorable perceptions of AI-assisted measurement,

particularly regarding workflow efficiency, consistency, and productivity. However, 82.5% emphasized the need for verification, while 61.7% expressed concern about overreliance. Nearly all respondents (99.2%) considered quality control important, indicating that perceived efficiency was accompanied by strong recognition of professional oversight and safety.

Table 3. Workflow perceptions of participants.

Measure	Positive, n (%)	Neutral, n (%)	Negative, n (%)
Workflow efficiency	82 (68.3)	30 (25.0)	8 (6.7)
Measurement-time reduction	74 (61.7)	37 (30.8)	9 (7.5)
Measurement consistency	79 (65.8)	29 (24.2)	12 (10.0)
Need for verification	99 (82.5)	17 (14.2)	4 (3.3)
Professional productivity	80 (66.7)	31 (25.8)	9 (7.5)
Concern about overreliance	74 (61.7)	39 (32.5)	7 (5.8)
Importance of quality control	119 (99.2)	1 (0.8)	0 (0.0)

Table 4. Workflow and professional-identity perceptions.

Construct	Positive (4–5)	Neutral (3)	Negative (1–2)
Workflow efficiency	82 (68.3%)	30 (25.0%)	8 (6.7%)
Measurement-time reduction	74 (61.7%)	37 (30.8%)	9 (7.5%)
Measurement consistency	79 (65.8%)	29 (24.2%)	12 (10.0%)
Need for verification	99 (82.5%)	17 (14.2%)	4 (3.3%)
Professional productivity	80 (66.7%)	31 (25.8%)	9 (7.5%)
Concern about overreliance	74 (61.7%)	39 (32.5%)	7 (5.8%)
Importance of quality control	119 (99.2%)	1 (0.8%)	0 (0.0%)
Human judgment remains essential	118 (98.3%)	2 (1.7%)	0 (0.0%)
AI changes expertise	59 (49.2%)	57 (47.5%)	4 (3.3%)
Risk of deskilling	34 (28.3%)	56 (46.7%)	30 (25.0%)
AI changes responsibilities	59 (49.2%)	42 (35.0%)	19 (15.8%)
Threat to professional role	10 (8.3%)	58 (48.3%)	52 (43.3%)
Professional expertise remains necessary	120 (100.0%)	0 (0.0%)	0 (0.0%)

3.4 Professional identity

The pattern in Table 4 indicates simultaneous recognition of changing expertise and continued importance of professional judgment. The deskilling item represents perceived risk rather than objective evidence of declining competence.

3.5 Trust and acceptance

High trust was represented in 55 records (45.8%), moderate trust in 51 (42.5%), and low trust in 14 (11.7%).

High AI acceptance was represented in 69 records (57.5%) as shown in Table 5.

The median trust score was 3.0 (IQR 3.0–4.0) among trained records and 3.0 (IQR 3.0–4.0) among untrained records.

3.6 Correlations

The results in Table 5 showed a strong positive association between perceived accuracy and trust

Table 5. Distribution of overall trust and high AI acceptance.

Measure	n	%
High trust (4–5)	55	45.8
Moderate trust (3)	51	42.5
Low trust (1–2)	14	11.7
High AI acceptance (4–5)	69	57.5

Table 6. Spearman rank correlations among prespecified study variables.

Association	ρ	p-value
Perceived accuracy ↔ trust	0.719	0.000
Frequent AI use ↔ workflow efficiency	0.435	0.000
Frequent AI use ↔ trust	0.328	0.000
Formal AI training ↔ trust	0.047	0.607

Table 7. Multivariable logistic regression for high AI acceptance.

Predictor	Adjusted OR	95% CI	p-value
Formal AI training	2.557	1.078–6.066	0.033
Frequent AI use	1.616	0.585–4.469	0.355
High workflow benefit	1.910	0.737–4.948	0.183
High perceived accuracy	4.373	1.712–11.173	0.002
Experience >10 years	0.816	0.343–1.938	0.644
High institutional support	1.014	0.402–2.561	0.977

Table 8-Qualitative themes from the interviews

Theme	Core meaning	Participant account
1. Automation redistributes expertise	AI reduces repetitive measurement but increases judgment about exceptions and quality.	“I spend less time tracing, but more time deciding whether the trace makes sense.”
2. Verification becomes a new competency	Checking machine output becomes an explicit professional task.	“The number appears quickly; my job is to know when it should not be trusted.”
3. Trust is conditional, not binary	Confidence depends on image quality, pathology, transparency, and prior system performance.	“I trust it on clean studies. Difficult studies make me slow down.”
4. Identity shifts from producer to supervisor	Participants describe a movement from manual measurement toward oversight, interpretation, and quality assurance.	“I am not losing the skill; I am using it differently.”
5. Organizational readiness shapes experience	Training, IT support, governance, and feedback channels influence whether AI feels enabling or burdensome.	“The software is only one part. Someone has to support the workflow around it.”

($p=0.719$, $p<.001$). Frequent AI use was moderately associated with workflow efficiency ($p=0.435$, $p<.001$) and weakly associated with trust ($p=0.328$, $p<.001$). Formal AI training was not significantly associated with trust ($p=0.047$, $p=.607$).

3.7 Multivariable logistic regression

Formal AI training and high perceived accuracy were significantly associated with the outcome, with adjusted odds ratios of 2.557 ($p=.033$) and 4.373 ($p=.002$), respectively. Frequent AI use, workflow benefit, experience, and institutional support were not statistically significant predictors. High perceived accuracy showed the strongest observed association among the predictors as shown in Table 7.

3.8 Qualitative themes

Five themes shown in Table 8 were developed from the interviews. The themes converge around a central interpretation: AI was experienced less as a replacement for professional expertise than as a change in where expertise is exercised. Participants described less manual production of measurements but more evaluation of measurement quality, exception handling, and responsibility for final outputs.

The findings therefore suggest that AI changes the location and visibility of expertise rather than eliminating the need for expertise.

Theme 1: Automation Redistributes Expertise

Participants described AI-assisted measurement as reducing repetitive technical activities while simultaneously increasing the importance of higher-level judgment. Automated tracing and measurement reduced the amount of time spent manually placing calipers, tracing chamber borders, and repeating routine measurements. However, participants emphasized that the availability of an automated value did not remove the need to determine whether the value was appropriate for the clinical and technical context.

One participant explained:

“I spend less time tracing, but more time deciding whether the trace makes sense.” (participant account)

Another participant described the change as a shift in the type of attention required during an examination:

“The software takes care of some of the routine work, but I have to pay more attention to whether the image is good enough for the software to make the right measurement.”

(participant account)

A third participant similarly emphasized that automation did not make technical knowledge irrelevant:

“I would not say that the machine replaces the skill. It means I use the skill differently because I am checking the result instead of creating every measurement from the beginning.” (participant account)

These accounts suggest that automation redistributed expertise from direct production toward evaluation and exception management. Participants continued to regard knowledge of cardiac anatomy, image quality, acquisition technique, and measurement principles as essential because these skills enabled them to recognize when an automated result was implausible. Thus, the perceived benefit of automation depended partly on the operator’s ability to understand the measurement being generated.

Theme 2: Verification Becomes a New Competency

A second theme concerned the emergence of verification as an explicit professional competency. Participants did not describe automated measurements as outputs that could simply be accepted without review. Instead, they viewed verification as an essential step between algorithmic measurement and final clinical documentation. This was particularly important when image quality was poor, cardiac anatomy was unusual, rhythm was irregular, or the automated boundary appeared inconsistent with the underlying image.

One participant stated:

“The number appears quickly; my job is to know when it should not be trusted.” (participant account)

Another explained:

“The important skill is not just knowing how to get the measurement. It is knowing when the AI has got it wrong and being confident enough to change it.” (participant account)

A further participant described verification as an increasingly routine part of professional responsibility:

“I check the automated measurement just as seriously as I would check something I measured myself. The fact that the computer produced it does not make me less responsible for the final number.” (participant account)

Participants therefore framed verification as more than a technical correction. It represented a form of professional accountability. AI could generate a measurement rapidly, but the echocardiographer remained responsible for determining whether that measurement was clinically and technically defensible. This suggests that implementation

programs should explicitly teach users how to recognize AI failure modes rather than assuming that familiarity with the software will automatically produce safe use.

Theme 3: Trust Is Conditional, Not Binary

Participants generally did not describe themselves as either trusting or distrusting AI. Instead, trust was conditional and context-dependent. Participants reported greater confidence in automated measurements when image quality was high, the cardiac anatomy was conventional, and the system had previously demonstrated reliable performance. Confidence decreased when studies were technically difficult or when the generated measurement differed noticeably from the participant's visual assessment. One participant summarized this distinction:

"I trust it on clean studies. Difficult studies make me slow down." (participant account)

Another participant explained:

"After using it for a while, you learn where it is usually reliable and where you need to be more careful. My trust depends on the situation." (participant account)

A third participant emphasized the importance of transparency and the ability to inspect the automated result: "I am much more comfortable accepting the measurement when I can see exactly what the system has traced and change it if necessary." (participant account)

These accounts indicate that successful implementation may depend on developing calibrated trust rather than maximizing trust. Participants appeared to value AI when it functioned as an editable assistant rather than an unquestionable authority. The ability to visualize, inspect, modify, and reject an automated measurement contributed to confidence in the technology. Conversely, uncertainty about how a measurement had been generated increased the perceived need for manual verification.

Theme 4: Identity Shifts from Producer to Supervisor

The fourth theme concerned changes in professional identity. Participants described a gradual movement away from viewing their expertise primarily in terms of manually producing measurements and toward a broader role involving supervision, quality assurance, interpretation, and decision-making. This transition was not necessarily perceived negatively. Several participants regarded the change as an opportunity to spend more time on aspects of echocardiography that require clinical reasoning and less time on repetitive technical tasks. One participant described this transition directly:

"I am not losing the skill; I am using it differently." (participant account)

Another participant stated:

"Before, being good at the job meant being very accurate and very fast with your measurements. Now it also means knowing whether the automated measurement is reasonable and when you need to intervene." (participant account)

A third participant described a broader change in how professional value was perceived:

"The machine can produce a number, but it cannot take responsibility for the study. I still have to make sure the examination is complete and that the measurements actually represent the patient." (participant account)

The accounts suggest that professional identity was being renegotiated rather than simply weakened. Participants continued to identify technical knowledge as important but increasingly linked expertise with oversight and judgment. This finding is relevant to education because students entering AI-enabled laboratories may need to understand that professional competence encompasses both the ability to perform measurements manually and the ability to supervise, verify, and appropriately challenge automated outputs.

Theme 5: Organizational Readiness Shapes Experience

The fifth theme demonstrated that individual attitudes toward AI were strongly connected to the organizational environment in which the technology was introduced. Participants emphasized that software performance alone did not determine whether AI was experienced as useful. Training, technical support, workflow design, management expectations, communication with the vendor, and mechanisms for reporting problems all influenced adoption.

One participant explained:

"The software is only one part. Someone has to support the workflow around it." (participant account)

Another participant highlighted the importance of practical training:

"We were shown how to use the buttons, but we needed more training on what to do when the system gets something wrong." (participant account)

A third participant emphasized the role of organizational responsiveness:

"If we report that the system is struggling with certain studies, there needs to be a process for someone to look at that problem. Otherwise, users just work around it themselves." (participant account)

These accounts indicate that AI implementation is an organizational process rather than a simple technology installation. Participants appeared more receptive when they received adequate training, had access to technical assistance, and were able to provide feedback about recurrent problems. Conversely, insufficient support could transform an intended efficiency intervention into an additional source of workload. Organizational readiness therefore appeared to influence not only whether AI was adopted but also how the technology was incorporated into professional routines.

Across the five themes, a consistent pattern emerged: AI-assisted measurement was experienced less as a replacement for professional expertise and more as a change in where and how expertise is exercised. Participants described a reduction in repetitive manual measurement but an increase in the importance of verification, exception recognition, image-quality assessment, and responsibility for the final output. Trust was described as conditional, with confidence depending on the technical and clinical circumstances of each examination. At the same time, participants' descriptions of professional identity suggested movement toward a supervisory and quality-assurance role rather than complete displacement of existing expertise. The findings also demonstrate that individual acceptance cannot be separated from organizational conditions. Training, technical support, governance, and opportunities for feedback shaped whether automation was perceived as enabling or burdensome. Taken together, the

themes suggest that successful AI integration requires organizations to recognize verification, judgment, and AI oversight as legitimate professional competencies. Rather than measuring implementation success solely through time saved, future evaluations should also examine how responsibility, cognitive workload, professional autonomy, and expertise are redistributed following AI adoption.

3.9 Mixed-methods integration

The joint interpretation showed convergence around four implementation concepts. Positive workflow perceptions corresponded with the workflow-accelerator theme; routine verification corresponded with human oversight; perceived changes in expertise coexisted with continued recognition of professional expertise; and the training/governance theme complemented the quantitative analysis by emphasizing informed reliance rather than simple software familiarity.

4. Discussion

The principal finding of this analysis is that AI-assisted measurement is most usefully conceptualized as an augmentation process rather than as a simple replacement of professional work. Frequent use coexisted with routine verification, while favorable workflow perceptions coexisted with concern about overreliance and endorsement of quality control. The analytical pattern therefore places professional judgment within, rather than outside, the AI-assisted workflow.

Table 7. Mixed-methods joint display linking quantitative findings with qualitative themes.

Quantitative finding	Qualitative theme	Integrated interpretation
82/120 positive workflow efficiency	AI as a workflow accelerator	Automation may reduce repetitive measurement burden and redirect attention toward review.
74/120 positive time reduction	AI as a workflow accelerator	Perceived time savings support an augmentation hypothesis; objective time was not measured.
97/120 usually verify outputs	Human verification remains central	Routine AI use coexists with active professional checking.
$\rho=0.719$ accuracy $\leftrightarrow$ trust	Human verification remains central	Trust is closely linked to perceived reliability and should remain calibrated.
59/120 report changed expertise; 120/120 retain expertise as necessary	Changing boundaries of expertise	Automation may redistribute expertise toward verification and interpretation.
Training OR=2.557	Training and governance shape adoption	Training is associated with acceptance in the model, while implementation also depends on governance and knowledge of limitations.

This interpretation is consistent with the direction of published echocardiographic AI research. Automated measurement studies have demonstrated meaningful reductions in measurement and processing time, while other work has shown that manual adjustment remains necessary under less favorable image conditions. Randomized workflow evidence has also demonstrated shorter examination times and expansion in the number of parameters analyzed with AI assistance. These findings provide a technical context for understanding why professionals may perceive both efficiency and verification as necessary components of the same workflow.

Perceived accuracy had the strongest correlation with trust in the analytical dataset ($\rho = 0.719$). This relationship is consistent with the concept of appropriate reliance: confidence is most useful when it corresponds to the demonstrated capabilities and limitations of an automated system. High trust should therefore not be interpreted as inherently desirable if it is accompanied by inappropriate reliance. (Astobiza & Ortega Lozano, 2025; de Camargo Catapan et al., 2025; Habib & Siddiqui, 2024; Nesa et al., 2025; Rosenbacke & Stuckler, 2024)

For echocardiographic AI, calibrated trust means that professionals should recognize when automated contours, measurements, or functional estimates are credible and when they require correction. Interfaces should support this process by allowing users to inspect source images, review automated tracings, correct outputs, and identify conditions under which the algorithm should not be relied upon.

Routine verification was represented in 97 of 120 records (80.8%). This pattern is important because verification should not automatically be interpreted as a failure of automation. Instead, verification can be the mechanism that preserves professional accountability in an automated workflow. (Astobiza & Ortega Lozano, 2025; Hirata & Kusunose, 2025; Olaisen et al., 2024; Rosenbacke & Stuckler, 2024; Sahashi et al., 2025; Sakamoto et al., 2026; Sun et al., 2026; Szasz et al., 2026)

The implication is that verification should be designed into the workflow. Training should include examples of failure modes, and governance should define which measurements require review, when manual correction is required, and how recurring errors are documented. Such processes are particularly important because automation bias can reduce vigilance when users become overly dependent on automated recommendations.

The professional-identity findings illustrate a distinction

between changing work and disappearing expertise. Records frequently indicated that AI changes expertise and responsibilities, yet professional judgment and expertise remained strongly endorsed. This suggests that the content of expertise may shift toward verification, exception recognition, contextual interpretation, and quality assurance. (Ayorinde et al., 2024; Habib & Siddiqui, 2024; Huotari et al., 2026; Vanamali & Dronamraju, 2025; Wang et al., 2023; Yousif et al., 2024)

The perceived deskilling concern should be interpreted carefully. A concern that routine manual skills may receive less practice is meaningful for education, but it does not demonstrate actual competence loss. Objective evidence would require longitudinal assessment of manual measurement accuracy, independent tracing ability, error recognition, and performance before and after sustained exposure to AI.

Formal training was included as a predictor of high AI acceptance, with an adjusted OR of 2.557. The training–trust correlation was $\rho = 0.047$, indicating that training should not be treated as the sole determinant of trust. (Ayorinde et al., 2024; de Camargo Catapan et al., 2025; Habib & Siddiqui, 2024; Huotari et al., 2026; Nesa et al., 2025; Scott et al., 2025; Vanamali & Dronamraju, 2025; Yousif et al., 2024)

A practical training program should therefore extend beyond software operation. It should explain intended use, limitations, image-quality dependencies, common failure patterns, verification requirements, escalation procedures, and the circumstances in which manual measurement should replace or override an automated result. Institutional governance should complement training through defined accountability, audit processes, performance monitoring, and update procedures.

The findings support a task-redistribution interpretation. When AI performs repetitive tracing or measurement, professional effort may be redirected toward reviewing image adequacy, checking automated outputs, resolving discrepancies, interpreting the examination, and maintaining quality. This may be beneficial when verification is efficient; however, the present analytical dataset does not provide objective examination-time or workload measurements.

Consequently, perceived time reduction should not be described as demonstrated time savings. Future empirical studies should separately measure acquisition time, post-acquisition measurement time, correction time, reporting time, and downstream report amendments.

For education, AI-assisted echocardiography should be taught as a human–AI collaboration rather than as an autonomous replacement process. Students should learn both how automated measurement works and how it can fail. Manual measurement skills remain important because professionals must be able to recognize implausible AI outputs and understand the measurement principles underlying automated results. (Ayorinde et al., 2024; Habib & Siddiqui, 2024; Heo & Chang, 2026; Huotari et al., 2026; Scott et al., 2025; Vanamali & Dronamraju, 2025; Wang et al., 2023; Yousif et al., 2024)

For research, future studies should combine subjective measures of trust and acceptance with observed verification behavior, correction rates, objective workflow times, expert agreement, image-quality stratification, and longitudinal competence assessment. Prospective qualitative studies should use primary interviews or focus groups to investigate how professionals define expertise and responsibility as automation becomes more integrated into routine echocardiography. (Ayorinde et al., 2024; Bodnari & Travis, 2025; Collins et al., 2024; Economou-Zavlanos et al., 2024; Habib & Siddiqui, 2024; Huotari et al., 2026; Lafitte et al., 2025; Mennella & Esposito, 2024; Moving beyond technical issues to stakeholder involvement, 2024; Olaisen et al., 2024; Park & Suh, 2024; Sahashi et al., 2025; Sakamoto et al., 2026; Shiokawa et al., 2024; Sun et al., 2026; Szasz et al., 2026; van Kessel et al., 2024; Yang et al., 2024; Yousif et al., 2024).

5. Limitations and Future Research

First, the dataset is an analytical teaching dataset rather than a prospectively recruited professional population. The reported percentages therefore describe the supplied records and cannot be generalized to echocardiographers or healthcare institutions. Finally, the source does not identify specific AI vendors, model versions, ultrasound platforms, or deployment environments. Because performance can vary by system, image quality, patient characteristics, and workflow, empirical implementation studies should include platform-specific validation and post-deployment monitoring. For future implementation, the key question is not simply whether AI is accepted, but whether it can be integrated in a way that supports calibrated trust, reliable verification, professional competence, and accountable workflow. Prospective empirical studies with recruited professionals, objective workflow measures, primary qualitative data, and longitudinal competency assessment are needed to test these hypotheses.

6. Conclusion

AI-assisted echocardiographic measurement has the potential to support workflow efficiency while preserving a central role for professional judgment. In the analytical dataset examined here, frequent use coexisted with routine verification, favorable workflow perceptions coexisted with concern about overreliance, and perceived accuracy was closely associated with trust and acceptance.

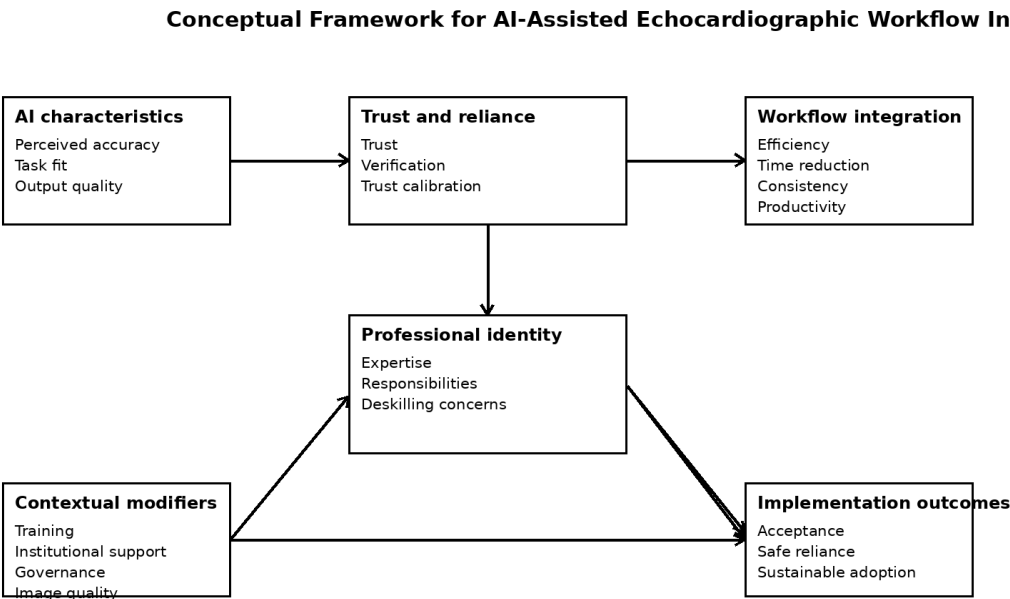


Figure 1. Conceptual framework linking AI characteristics, trust and reliance, workflow integration, professional identity, contextual modifiers, and implementation outcomes. The framework is conceptual and does not imply causality in the analytical dataset.

The mixed-methods framework further suggests that AI may redistribute expertise toward verification, interpretation, exception recognition, and quality control rather than simply eliminating professional work.

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