PANEL DISCUSSION

Advancing Structural Heart Care With Automation and AI

How automation and artificial intelligence can be used to detect disparities, support patients, and strengthen shared decision-making in structural heart intervention.

With Haytham Allaham, MD; Megan Coylewright, MD, MPH, FACC, FSCAI; and Mukta Srivastava, MD

Haytham Allaham, MD
Assistant Professor
University of Maryland School of Medicine
Baltimore, Maryland
hallaham@som.umaryland.edu

Megan Coylewright, MD, MPH, FACC, FSCAI
Structural Interventional Cardiologist
Essentia Health
Duluth, Minnesota
coylewrightmd@gmail.com

Mukta Srivastava, MD
Associate Professor
University of Maryland School of Medicine
Baltimore, Maryland
msrivast@som.umaryland.edu

How is your institution currently using artificial intelligence (AI) for structural heart intervention?

Dr. Coylewright: AI can be used in a variety of ways to improve care for patients eligible for a structural heart intervention, and a place to start is in the identification and management of currently underrecognized and undertreated patients with valvular heart disease. For example, there are very specific disparities that have been outlined regarding access to care for patients with severe aortic stenosis (AS). We have been undertreating women and patients of racial and ethnic minority groups, and it has led to disparities in health outcomes. Use of AI to send automated notifications of echocardiogram results showing severe AS can play a critical role in the detection and management of patients with AS.

The use of automated alerts to notify clinicians of patients who may benefit from a structural heart intervention is already proven in the research literature.[1,2] Tanguturi et al published a pragmatic, cluster randomized clinical trial evaluating use of electronic notifications to detect patients with AS.[1] This paper showed that by identifying patients who had a transthoracic echocardiogram with a class I indication for aortic valve replacement and then generating automated alerts to clinicians, there were several key outcomes. The proportion of patients treated significantly increased, and significant disparities in use of aortic valve replacement for men and women were reduced. Kirby et al evaluated use of electronic health record (EHR) alerts to provide feedback and recommendations for specialist referral for severe AS. After implementation, the referral rate was 97.5%, which was a 24.6% increase ($P < .001$).[2]

As cardiovascular clinicians, we do our best to offer therapies equitably to every patient who comes to us. A lot of the treatment biases that we have are quite unconscious.

So, having some automation in the process of detection and management may be helpful to address some of these barriers to treatment.

We are all eager to have access to more programs using AI that help us be increasingly specific about how we select patients who are appropriate to be evaluated in the valve clinic. It will be important that these tools are codesigned with clinicians and patients to ensure that they are keeping patients at the center.

Dr. Srivastava: At our institution, AI has been advanced most in the area of preprocedural imaging for structural interventions. All patients typically undergo imaging before their implant, often with cardiac CTA, which we can then upload into software that can provide three-dimensional models of the left atrial appendage, elucidating optimal landing zones and device sizing. Ultimately, this helps streamline the procedure, improves procedural success, and reduce both the number of devices deployed and overall resource use.

At which stages of the structural heart workflow—evaluation, imaging, procedural planning, or follow-up—do you anticipate AI-supported tools being most impactful?

Dr. Allaham: AI has the potential to be impactful across the entire transcatheter aortic valve replacement (TAVR) workflow—from evaluation to long-term follow-up. We are already seeing promising data demonstrating its ability to automate the diagnosis of severe AS on echocardiography, enhance risk stratification, optimize preprocedural CT planning, and improve outcome prediction.[3-6]

In my view, the most transformative impact will likely occur at the stages of imaging analysis and procedural planning. AI can standardize measurements across complex anatomy, reduce interobserver variability, and extract subtle morphologic and hemodynamic features that may not be readily apparent to the human eye. This becomes particularly valuable in anatomically challenging scenarios, such as borderline annular sizing, low coronary heights, and complex left ventricular outflow tract anatomy, where small differences can significantly affect outcomes.

As these tools become more integrated into routine practice, they will streamline workflow, reduce intraprocedural trial and error, and enhance procedural efficiency. Ultimately, the greatest value may not simply be operational—it will be clinical. AI-driven risk modeling and personalized outcome prediction will allow us to have more precise, patient-specific discussions about procedural risks and expected benefits. That level of personalization supports shared decision-making and leads to more informed, value-based care for patients with severe AS.

Dr. Srivastava: In the left atrial appendage workflow in the near term, we hope to employ AI to inform optimal patient selection to identify patients most likely to sustain benefits of the device and anticipate those with a high chance for procedural complication, as well as anatomies with high risk for peridevice leak or device-related thrombus. Another vision for application of AI in this space would include developing interfaces to use with trainees to allow for improved hands-on exposures prior to implants in patients.

What are the key challenges with integrating AI or machine learning software into clinical practice? What considerations are unique to implementing these tools within a TAVR program?

Dr. Allaham: Integrating AI into clinical practice presents both technical and cultural challenges. In TAVR specifically, the next phase of AI adoption must prioritize transparency, reproducibility, and equity. Models need robust external validation across diverse patient populations, standardized reporting of development methods and limitations, and prospective evaluation of real-world clinical impact. Without that level of rigor, it becomes difficult to build trust among clinicians.

Another key consideration is interpretability. Physicians are unlikely to rely on "black box" algorithms in high-stakes structural interventions unless they understand how outputs are generated and where limitations exist. Education is therefore critical—not just awareness of available tools but also meaningful training on how to interpret AI-derived risk estimates and integrate them into decision-making without overreliance.

Within a TAVR program, there are additional workflow considerations. These tools must integrate seamlessly into existing imaging platforms, heart team discussions, and procedural planning software. Adoption will be limited if implementation disrupts workflow instead of enhancing efficiency.

From an evidence standpoint, while early data supporting AI in TAVR are promising, our field remains firmly grounded in evidence-based medicine. Broader prospective studies demonstrating improved outcomes, procedural efficiency, or cost-effectiveness will be essential before widespread adoption.

Finally, financial considerations cannot be ignored. The up-front cost of implementation, software integration, and training must be justified by measurable clinical and operational value. I suspect that as the technology matures and commercial competition increases, cost-effectiveness will become clearer, particularly if AI demonstrably reduces complications, procedural variability, or resource utilization. Ultimately, successful integration will depend not only on technologic innovation but also on trust, validation, workflow alignment, and measurable patient benefit.

How might automation and AI help address disparities for structural heart disease in general? And for AS diagnosis, referral patterns, and access to TAVR?

Dr. Coylewright: We know that there are disparities in care when it comes to the treatment of AS, whether via TAVR or surgical aortic valve replacement (SAVR). Disparities are seen in terms of gender, race and ethnicity, and geography. We continue to focus on geography specifically for two reasons: (1) geography often helps us predict areas where racial/ethnic disparities in care begin, and (2) there is a significant disparity of treatment among patients who live in rural areas.[7,8]

This is currently true where I practice at a rural hospital in northern Minnesota. We've been thinking about how we can continue to focus on bringing best practices and effective interventions to our patients in our rural location. I am a member of the steering committee for the large ALERT study investigating the role of AI-powered EHR notifications to improve care delivery for patients with AS and mitral regurgitation. Our methods paper is published, and our study outcomes were presented at the American College of Cardiology Scientific Sessions in March 2026.[1,9]

However, there is a role for AI in disease detection and management that goes above and beyond this. There is very early work focused on how to use AI to detect valve disease via electrocardiograms, how machine learning can optimize our interpretation of echocardiographic data (especially the challenging low-flow, low-gradient patient), and using AI to predict progression of disease, a key interest noted by our patients.

Based on patient forums involving patients with AS and similar work in tricuspid regurgitation (TR), early patient engagement in their valvular heart disease journey is both patient-centered and patient-desired. I recently published a paper on meeting with TR patients and asking about their goals and preferences, not just for treatment of their disease but also for how we partner with them and coproduce their health care.[10] In these forums, patients emphasized that they would like more information earlier in the disease process.

Our goal is to use AI as a tool to identify patients with risk factors for AS and have the hospital system reach out to them directly with a variety of forms of education. We hope that patients can come to the clinic informed about the disease process and engage as partners in their care. Ultimately, it is not enough to detect the disease; we want to ensure that patients are informed so they are ready to share their goals and preferences and participate in shared decision-making.

Given that many AI models are trained on data sets lacking racial, socioeconomic, and sex diversity, what safeguards are needed to ensure unbiased and clinically reliable predictions in TAVR care?

Dr. Coylewright: This is a really important question. In the development of AI models, are we baking in any biases? These could be from the data set itself or from those designing our earliest models. Thus, it's important to have a variety of people working together to ensure that the AI models we are developing treat people equitably, with safeguards in place, and do not provide greater distance between us and our patients.

There is a risk with AI. It can make the work we do easier and faster, but this is where we can fall into a trap. Making decisions with patients and caring for them throughout their health care journey is not typically easy or fast—it's messy and complex, and it requires a lot of human-to-human interactions, the tough work of listening.

As we are designing AI models in our own health system and thinking about how best to partner with our patients, we need to keep these considerations in mind. The best way to do this is to have different voices at the table—clinicians, advanced practice clinicians, and nurses, but also patients and families. They can help us understand what drives patients further away from connection with the health care system versus bringing them in.

It's very important that we look at who is designing the models and for what purpose. In health care, our goals are ideally different than marketing, for example. We want tools that bring us closer in human relationship to our patients—not further away.

Looking ahead, how could predictive AI models transform long-term valve surveillance, and how do you envision the TAVR landscape evolving over the next decade?

Dr. Allaham: Valve failure after TAVR is fortunately uncommon, but durability is still something we think about carefully, especially as we're treating younger and lower-risk patients who are expected to live many years after their procedure. One of the challenges is that predicting which valve might fail isn't straightforward. It's rarely just one factor—it's usually a combination of patient characteristics, anatomy, imaging findings, and procedural details. That's where AI becomes very interesting.

AI can look at large amounts of data at once—imaging, clinical information, procedural variables—and identify patterns that may not be obvious to us in real time.[11] It can help flag patients who may be at higher risk of valve dysfunction, leaflet thrombosis, or subtle changes that could progress over time. In some cases, AI tools can even simulate what the valve might look like after implantation and help anticipate potential problems before they occur.

The real value isn't just prediction—it's earlier detection and better follow-up. If we can identify valve dysfunction sooner, we can adjust medical therapy, optimize anticoagulation strategies, and monitor patients more closely. That ultimately helps prevent complications and protects long-term outcomes.

Dr. Coylewright: This question is about technical precision. AI models that are designed to help us understand and better predict how the first valve will land and fit within the patient's anatomy will help us determine a few different things. First is how valve durability is impacted by the type and size of valve selected, the degree of calcification, and other anatomic factors. Currently, we have very generic rules that lack a level of personalization and prediction that may be more possible with AI-driven models. Right now, we will look at that TAVR once a year with echocardiography and a sudden rise in valve gradient will be a surprise; perhaps this can be predicted and thus prevented.

Notably, we do have data showing that both TAVR and SAVR perform very well at 7 years. Still, there are patients who develop structural valve deterioration, which may be related to which valve type and size was chosen for a specific anatomy or how a valve was implanted, including pre- or post–balloon dilation. Learning models that incorporate thousands of patient outcomes may help us not only simulate acute procedural outcomes but also predict longer term outcomes, which is critical for the lifetime management of valve disease.[12,13]

When the valve does fail, the ability to predict what treatment should be offered is another potential avenue for AI. Right now, when we put in the index valve, there are only crude ways to predict how we might be able to serve this patient for a second valve implantation. We look at things like annular size, the sinuses of Valsalva, and degree of calcification, but it is not a very sophisticated process. When sitting down as a heart team for a case of AS—considering TAVR versus SAVR or choosing between multiple valve platforms—it would be terrific if we could quickly visualize the way the first valve will land, the shape it will take, and its hemodynamics, and the same for the second valve. This would provide us with the kind of precise selection of an index valve that will optimize valve performance and minimize the need for multiple valve interventions.

Further, it would inform our shared decision-making and allow greater clarity in our communication with patients about why, in some anatomies, an initial SAVR followed by a TAVR may be more likely to accomplish their long-term goals. It could also give us a better understanding of which patients are very low risk for a future TAVR explant, offering younger patients—who are balancing work and family responsibilities—the option of a minimally invasive procedure now with surgery later.

Overall, I think the use of AI here can provide a wealth of information for us and our patients, allowing us to sit down with them and say (in more patient-friendly terms), "Here is what we predict based on an informed modeling of the optimized lifetime management of your aortic valve disease."

How might AI improve communication and collaboration across the multidisciplinary heart team?

Dr. Coylewright: There are so many ways that we can improve communication across our multidisciplinary team. I'm leading one of the largest studies of the heart team ever performed, called the EVOLVE study. It is a mixed-method study, meaning it is both quantitative (who is involved, the time spent planning) and qualitative (the attitudes and beliefs around how they interact with each other and how that could improve over time).

Post-COVID, many have moved heart teams to completely virtual models. They are communicating with a mix of in-person and virtual attendance, mixed in with EHR chats, some texting and some phone discussions, and with a lot of multitasking and split attention during meetings. Not many sites are physically meeting together in clinic with the patient. There are a lot of opportunities for miscommunication in our current model, and there are opportunities for improving this through AI. One way is through limiting the time that physicians are spending doing procedural planning alone at their desk. Having our own in-hospital models to predict valve fit and function would give us the necessary time to sit down together as a heart team, working on our collaborative skill sets. These human-to-human interactions are so necessary to avoid burnout and lead to professional satisfaction. Importantly, they help us develop a true expert team that enjoys working together. These are the things that are going to drive success in health care.

Ultimately, our challenge will be in allowing technology to bring us closer together rather than push us further apart. We have prior examples of this happening, so it really will depend on an intentionality of how we use AI tools. Much of this will start by reducing the time spent on planning and optimizing how we communicate with each other, both to avoid duplication of efforts and to ensure we have the time to sit down together at the table.

What should the primary research priorities be for AI in structural interventions in the next decade?

Dr. Srivastava: As AI is incorporated into procedural practice, we should engage experienced proceduralists alongside trainees to prevent deskilling and ensure these technologies enhance rather than erode clinical expertise. Deskilling, which refers to the decay of critical analysis skills that are outsourced to AI and automation or failure to develop these cognitive muscles due to early adoption of technology, can lead to downstream effects that may be difficult to quantify and may only surface during inevitable malfunctions of technology and during the aberrant and unusual cases. Retaining the ability to analyze and adapt fluidly will ultimately optimize the potential of AI. A recent article by Budzyń et al showed a reduction in adenoma detection rate by endoscopists after withdrawal of AI software after it had briefly been adopted, demonstrating the potential for deskilling to occur as AI is integrated in practice.[14] Research priorities should include mechanisms to augment training that retains critical analysis skills as well as mechanisms to mitigate deskilling of proceduralists.

Dr. Allaham: AI research in structural heart disease is growing rapidly, and we're already seeing meaningful progress across diagnosis, imaging interpretation, risk stratification, procedural planning, and outcome prediction. Our group recently wrote a comprehensive review summarizing the current clinical application of AI in structural heart disease, and that manuscript has been accepted in *Journal of the Society for Cardiovascular Angiography & Interventions*.

Looking ahead, I think the key research priorities over the next decade, and especially in TAVR, should focus on moving from "promising models" to tools that are truly reliable, fair, and clinically actionable.

First, we need stronger validation and generalizability. Many algorithms perform well in single-center or curated data sets, but the next step is demonstrating consistent performance across different hospitals, scanners, workflows, and diverse patient populations.

Next, equity and bias must be front and center. If AI tools are trained on nonrepresentative data, they risk worsening disparities rather than improving care. Ensuring fairness across sex, race/ethnicity, socioeconomic status, and anatomic variability will be essential.

I see major opportunity in improving preprocedural planning and procedural simulation, particularly for TAVR and transcatheter mitral interventions, where predicting complications, optimizing valve sizing/positioning, and anticipating coronary or conduction issues could meaningfully improve safety and efficiency. AI has been well studied in diagnosis, risk stratification, and outcome prediction, with meaningful progress in each of these areas. However, there is still substantial opportunity in preprocedural planning and procedural simulation. Moving toward reliable procedural simulation would shift us from reactive decision-making to a more predictive, strategy-driven approach, ultimately improving safety and efficiency.

Although TAVR has been the main focus so far, there is enormous unmet potential in other structural interventions such as mitral transcatheter edge-to-edge repair, transcatheter mitral valve replacement, tricuspid transcatheter edge-to-edge repair/transcatheter tricuspid valve repair, and left atrial appendage occlusion. These procedures have complex anatomy and imaging demands, and AI could help standardize planning and reduce variability in outcomes.

Finally, to truly change practice, we need prospective evidence, ideally including randomized clinical trials, showing that AI improves outcomes, decision-making, efficiency, or cost-effectiveness in real-world care. Alongside research, education matters. Incorporating core AI concepts into training for medical students, residents, and fellows will help clinicians use these tools appropriately and confidently as they become part of routine structural heart practice.

If we approach AI with rigor, transparency, and a commitment to equity, it has the potential to fundamentally enhance how we plan, perform, and follow structural interventions. Ultimately, the goal is not just smarter technology, but better, safer, and more personalized care for our patients. ■

1. Tanguturi VK, Abou-Karam R, Cheng F, et al. Electronic provider notification to facilitate the recognition and management of severe aortic stenosis: a randomized clinical trial. Circulation. 2025;151:1498-1507. doi: 10.1161/CIRCULATIONAHA.125.074470
2. Kirby AM, Kruger B, Jain R, et al. Using clinical decision support to improve referral rates in severe symptomatic aortic stenosis: a quality improvement initiative. Comput Inform Nurs. 2018;36:525-529. doi: 10.1097/CIN.0000000000000471
3. Krishna H, Desai K, Slostad B, et al. Fully automated artificial intelligence assessment of aortic stenosis by echocardiography. J Am Soc Echocardiogr. 2023;36:769-777. doi: 10.1016/j.echo.2023.03.008
4. Strom JB, Playford D, Stewart S, Strange G, et al. An artificial intelligence algorithm for detection of severe aortic stenosis: a clinical cohort study. JACC Adv. 2024;3:101176. doi: 10.1016/j.jacadv.2024.101176
5. Wang M, Niu G, Chen Y, et al. Development and validation of a deep learning-based fully automated algorithm for pre-TAVR CT assessment of the aortic valvular complex and detection of anatomical risk factors: a retrospective, multicentre study. EBioMedicine. 2023;96:104794. doi: 10.1016/j.ebiom.2023.104794
6. Russo MJ, Elmariah E, Kaneko T, et al. Machine learning identification of modifiable predictors of patient outcomes after transcatheter aortic valve replacement. JACC Adv. 2024;3:101116. doi: 10.1016/j.jacadv.2024.101116
7. Cené CW, Ansell DA, Chowkwanyun M, et al. Pursuing health equity in the United States. N Engl J Med. 2025;393:e30. doi: 10.1056/NEJMp2514402
8. GBD US Health Disparities Collaborators. Healthy life expectancy by county, race, and ethnicity in the USA, 2009-19: a systematic analysis of health disparities. Lancet Reg Health Am. 2025;45:101064. doi: 10.1016/j.lana.2025.101064
9. Batchelor WB, Lindman BR, Coylewright M, et al. A randomized trial evaluating automated notifications for the identification and treatment of aortic stenosis and mitral regurgitation: the ALERT study. J Soc Cardiovasc Angiogr Interv. Published online November 18, 2025. 10.1016/j.jscai.2025.104040
10. Coylewright M, Alston M, Arnold SV, et al. Patient-reported goals in tricuspid regurgitation: a qualitative analysis of patient and care partner perspectives. JACC Adv. 2025;4:101982. doi: 10.1016/j.jacadv.2025.101982
11. Tomii Y, Shiri I, Baj G, et al. Multimodal machine learning-based technical failure prediction in patients undergoing transcatheter aortic valve replacement. JACC Adv. 2025;4:102168. doi: 10.1016/j.jacadv.2025.102168
12. Leon MB, Mack MJ, Pibarot P; PARTNER 3 investigators. Transcatheter or surgical aortic-valve replacement in low-risk patients at 7 years. N Engl J Med. 2026;394:773-783. doi: 10.1056/NEJMoa2509766
13. Forrest JK, Yakubov SJ, Deeb GM, Reardon MJ; Evolut Low Risk Trial Investigators. Six-year outcomes after transcatheter vs surgical aortic valve replacement in low-risk patients with aortic stenosis. J Am Coll Cardiol. Published online February 16, 2026. doi: 10.1016/j.jacc.2026.02.5063
14. Budzyń K, Romańczyk M, Kitala D, et al. Endoscopist deskilling risk after exposure to artificial intelligence in colonoscopy: a multicentre, observational study. Lancet Gastroenterol Hepatol. 2025;10:896-903. doi: 10.1016/S2468-1253(25)00133-5

Disclosures
Dr. Allaham: None.
Dr. Coylewright: Consultant to Edwards Lifesciences, Medtronic, Boston Scientific, Recor Medical, and Alleviant.
Dr. Srivastava: None.