ASME Journal of Applied Mechanics
Online journal at:
https://asmedigitalcollection.asme.org/appliedmechanics

A Perspective on Democratizing Mechanical Testing: Harnessing Artificial Intelligence to Advance Sustainable Material Adoption and Decentralized Manufacturing

Christos E. Athanasiou[1]
Daniel Guggenheim School
of Aerospace Engineering,
Georgia Institute of Technology,
Atlanta, GA 30332
e-mail: athanasiou@gatech.edu

Xing Liu
George W. Woodruff School
of Mechanical Engineering,
Georgia Institute of Technology,
Atlanta, GA 30332;
Department of Mechanical
and Industrial Engineering,
New Jersey Institute of Technology,
Newark, NJ 07102
e-mail: xing.liu@me.gatech.edu

Huajian Gao[1]
Mechano-X Institute,
Applied Mechanics Laboratory,
Department of Engineering Mechanics,
Tsinghua University,
Beijing 100084, China
e-mail: gao.huajian@tsinghua.edu.cn

Democratized mechanical testing offers a promising solution for enabling the widespread adoption of recycled and renewably sourced feedstocks. Locally sourced, sustainable materials often exhibit variable mechanical properties, which limit their large-scale use due to tight manufacturing specifications. Wider access to mechanical testing at the local level can address this challenge by collecting data on the variable properties of sustainable feedstocks, allowing for the development of appropriate, uncertainty-aware mechanics frameworks. These frameworks are essential for designing custom manufacturing approaches that accommodate variable local feedstocks, while ensuring product quality and reliability through post-manufacturing testing. However, traditional mechanical testing apparatuses are too costly and complex for widespread local use by individuals or small, community-based facilities. Despite promising efforts over the past decade to develop more affordable and versatile testing hardware, significant limitations remain in their reliability, adaptability, and ease–of-use. Recent advances in artificial intelligence (AI) present an opportunity to overcome these limitations by reducing human intervention, enhancing instrument reliability, and facilitating data interpretation. AI can thus enable the creation of low-cost, user-friendly mechanical testing infrastructure. Future efforts to democratize mechanical testing are expected to be closely linked with advancements in manufacturing and materials mechanics. This perspective paper highlights the need to embrace AI advancements to facilitate local production from sustainable feedstocks and enhance the development of decentralized, low-/zero-waste supply chains. [DOI: 10.1115/1.4066085]

Keywords: democratized mechanical testing, artificial intelligence, renewable and recycled materials, mechanics of sustainable materials, zero-waste supply chains, mechanical properties of materials

1 Democratized Mechanical Testing for Circular and Local Production From Sustainable Feedstocks

Transition from linear to circular economic models is key to addressing the global climate crisis [1–3]. The existing, linear "take-make-waste" production and consumption patterns heavily rely on fossil fuels, resulting in substantial greenhouse gas emissions, resource depletion, and pollution issues. The current response to these social and environmental challenges has so far mostly focused on transitioning to renewable energy and improving energy efficiencies. These measures, though critical, can only partially resolve the climate problem, addressing about 55% of the generated emissions [1]. The remaining emissions arise from the long, complex, and wasteful supply chains. Therefore, a transition to circular, decentralized supply chains, where resources are reused and regenerated, will be desired (Fig. 1) [1,2].

Transitioning to decentralized supply chains and local production using sustainable feedstocks requires two key factors: locally sourced materials from recycled and/or renewable feedstocks and easily accessible manufacturing tools and facilities. Using local raw materials radically reduces transportation costs and related carbon footprints. The use of abundant renewable resources or recycled feedstocks, which have lower economic or environmental costs compared to virgin materials, enhances community resilience and resource security. In parallel, decentralized manufacturing facilities on-demand production, minimizing waste, removing economic

[1]Corresponding authors.

Contributed by the Applied Mechanics Division of ASME for publication in the Journal of Applied Mechanics. Manuscript received July 7, 2024; final manuscript received July 14, 2024; published online August 21, 2024. Tech. Editor: Pradeep Sharma.

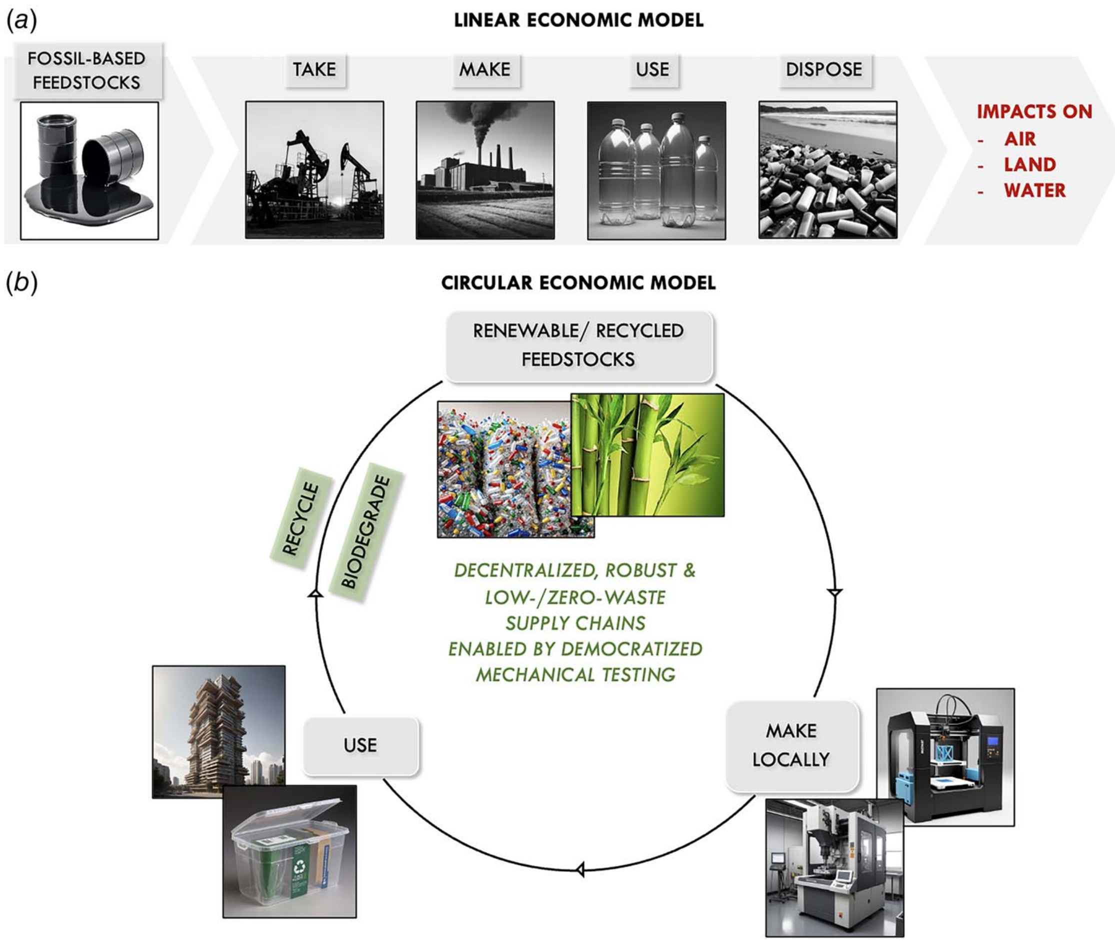

Fig. 1 Comparison of a linear fully circular urban production model (*a*) and a circular one based on manufacturing with renewable and recycled materials (*b*). Democratized mechanical testing is critical for the characterization of sustainable, highly heterogeneous feedstocks which are necessary for creating decentralized, robust, and low-/zero-waste supply chains.

barriers for new manufacturers and smaller-scale production, and bringing production closer to consumption. Recent technological advancements in digital manufacturing have made decentralized manufacturing feasible [4].

Nevertheless, manufacturing with locally sourced recycled and/or renewable materials is currently inhibited by feedstock variability, especially in terms of their mechanical properties, as their quality is affected by several factors including seasonality, climatic conditions, and recycling cycles [5–8]. For example, although wood is a renewable resource, wood feedstocks of the same species can exhibit 22% difference in elastic modulus and 34% difference in toughness when grown under varying moisture conditions [9]. Such variability is also present in recycled plastics which are usually contaminated with impurities introduced during their life cycles and recycling processes. Impurities (e.g., color additives or fragrances) can lead to polymer chain scission, entanglement, as well as side-product formation, including carbon dioxide, water, and carboxylic acid during the mechanical recycling process [10], and can eventually result in obtaining a wide range of mechanical properties. Therefore, even though recycled and renewable materials may match or even exceed the mechanical performance and functionalities of their synthetic or virgin counterparts [11], the large uncertainty in their mechanical properties limits their large-scale utilization considering the tight production specifications set by manufacturing industries.

Democratized mechanical testing can play a key role in overcoming this challenge. Offering wider accessibility to mechanical testing at the local level can enhance the collection of critical information about the above-described heterogeneities of locally sourced sustainable materials. This information, combined with the latest advancements in multiscale modeling, can guide product design and manufacturing, resulting in customized, adaptive manufacturing approaches capable of accommodating variable feedstock properties. Such manufacturing approaches can be complemented by post-manufacturing mechanical testing to ensure product quality and production reliability.

This perspective discusses the challenges and opportunities to enable circular production from sustainable feedstocks emphasizing the democratization of mechanical testing as a key starting point. Existing challenges and opportunities to democratize mechanical testing are identified together with prospects on how to overcome these challenges through recent developments in artificial intelligence (AI). The role of new mechanics and tailored manufacturing approaches in this process is considered, highlighting their integration with mechanical testing and AI. This showcases a pathway toward a future where the solid mechanics community actively aligns its efforts with the United Nations (UN) sustainable development goals.

2 Challenges and Opportunities Toward Democratized Mechanical Testing

Although democratizing mechanical testing could revolutionize local manufacturing with sustainable feedstocks, traditional testing apparatuses, like those used for tensile and flexural testing, remain largely inaccessible to individuals or small community-based manufacturing facilities. This is primarily due to their high cost, and also because of their complexity, the need for human intervention, and the requirement for specialized testing environments and high-throughput testing in certain cases.

Mechanical testing infrastructure typically consists of hardware required for performing the test and acquiring the data, and software for data analysis and property evaluation. For macroscale testing, conventional equipment is used, e.g., Instron or MTS machines, whose price ranges from \$10,000 to \$100,000 depending on involved features. Test specimens are prepared usually following American Society for Testing and Materials or International Organization for Standardization standards, in which property evaluation is also standardized [12]. For samples that do not fit the requirements of these standards, i.e., unconventional shapes or small dimensions, standardized procedures for mechanical characterization are largely missing [13–15]. Nanoindentation-based testing instruments typically incur a significant financial investment, with prices ranging from approximately \$100,000 to \$300,000. Additionally, these instruments often necessitate the use of advanced supplementary tools for sample preparation, such as focused-ion beams, sophisticated laser systems, and lithographic processes. The cumulative investment for such equipment can surpass \$1,000,000, leading to substantial ongoing operational expenses [16]. Furthermore, for the characterization of nonstandard specimens, computational modeling, which typically requires proprietary simulation software, such as commercial finite element method packages, is needed to interpret experimental data and extract accurate mechanical properties. Such software requires acquisition of expensive licenses and considerable domain expertise.

Several efforts have been made to develop more affordable and versatile testing hardware during the last decade (Fig. 2) [17,18]. Amend and Lipson [19] developed a low-cost tensile testing system known as “Freeloader” (Fig. 2(*b*)). This system offers a load capacity of 5 kN, with an accuracy of 0.02%, for a cost of less than \$4000. Steuben et al. [20] improved Freeloader by introducing an electrohydraulic actuator to increase its load capacity to 20 kN and meet the requirement for testing stiffer materials. The cost was further reduced to \$2500, while commercially available testing machines of comparable specifications range in cost from \$17,000 to \$26,000 [19,21]. High-strain-rate mechanical testing instruments [22], for characterizing materials’ response to extreme conditions [13,23] or educational purposes [24], are currently being developed by the engineering mechanics community.

These efforts, though promising, still have considerable room for improvement (Fig. 2). First, the *reliability* of new testing instruments, such as Freeloader [18], is a major concern. Calibration of these instruments can be labor-intensive. Second, the *adaptability* and *ease-of-use* of testing instruments to complex loading conditions, specimen geometries and sizes, and temporospatial variations in material properties, are poor [25]. Third, the accompanying *open-access* software for autonomous design of experiments, control of instruments, and analysis of measurements is largely underdeveloped. In light of recent advances in AI, coupled with the efforts of the engineering mechanics community to make the best use of it [26–41], these issues can be significantly remediated.

2.1 Enhancing Democratized Mechanical Testing Via Artificial Intelligence. The primary purpose of employing AI in advancing democratized mechanical testing is to minimize human intervention required in this process. For example, to introduce a new, low-cost testing instrument or method, extensive verification efforts and multiple iterations would be needed to ensure reliability. These processes can be expedited with the assistance of AI. AI can enable autonomous control of the instruments and conduct millions of validation tests with unprecedented precision and efficiency. Additionally, AI can learn from the collected data the correlation between instrument design and reliability and eventually contribute to the iterative design of new instruments and methods. Finally, AI can learn how measurement errors accumulate during the service time of the instrument and can potentially bypass them by correcting the raw data. Thus, the frequency of routine instrument

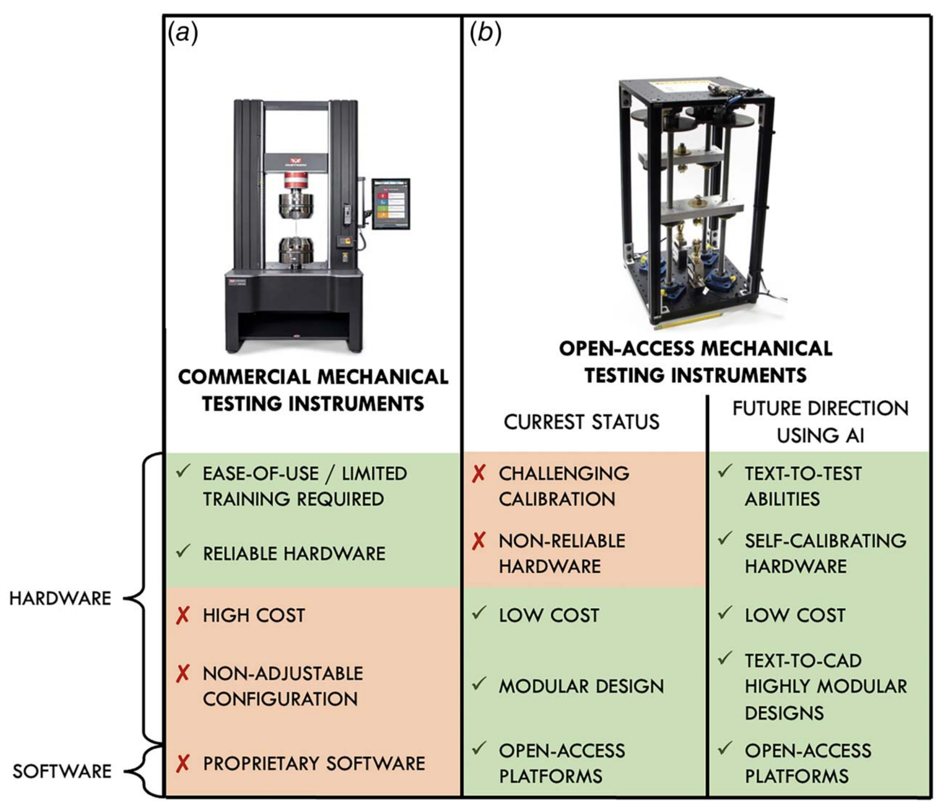

Fig. 2 Current challenges of commercial versus open-access instrumentation for mechanical testing and future opportunities by the incorporation of AI

calibration can be decreased, leading to significant savings in time and cost for extensive mechanical testing operations.

Mechanical testing of sustainable materials requires expertise in the design of experiments. For example, to explore the viscous properties of recycled plastics, a well-chosen combination of loading profiles can significantly reduce the required experimental effort. For materials exhibiting spatial variations in their properties, an optimized choice of sampling points can provide a more comprehensive description of such variations. AI frameworks, e.g., active learning and generative models, can be used to optimize the experimental designs and create self-evolving libraries of testing protocols that can adapt to various practical scenarios [29].

Conducting experiments, the most cost- and expertise-intensive step in mechanical testing, can also be transformed by AI. Through AI frameworks, data from multiple sources (such as data collected from force and optical sensors) can be processed simultaneously to achieve more precise control of instruments. Thus, experimental success rates that surpass those of skilled experimentalists can be potentially achieved through AI. This can significantly enhance high-throughput mechanical characterization of heterogeneous materials, especially under challenging testing conditions.

Another crucial aspect that AI can contribute to is data interpretation. The use of nonstandard specimens exhibiting complex geometries might be unavoidable in some cases when characterizing recycled/renewable feedstocks at small or community-based manufacturing facilities due to practical considerations or limited resources. In such scenarios, it is challenging to extract the required mechanical properties experimentally without specific analytical or semi-analytical solutions in place. Therefore, a new class of data interpretation solutions based on machine learning (ML) models has been developed to overcome this challenge [27–29]. ML models are capable of establishing an accurate correlation between the experimentally obtained quantities and material properties of interest, based on reference experimental and/or simulation

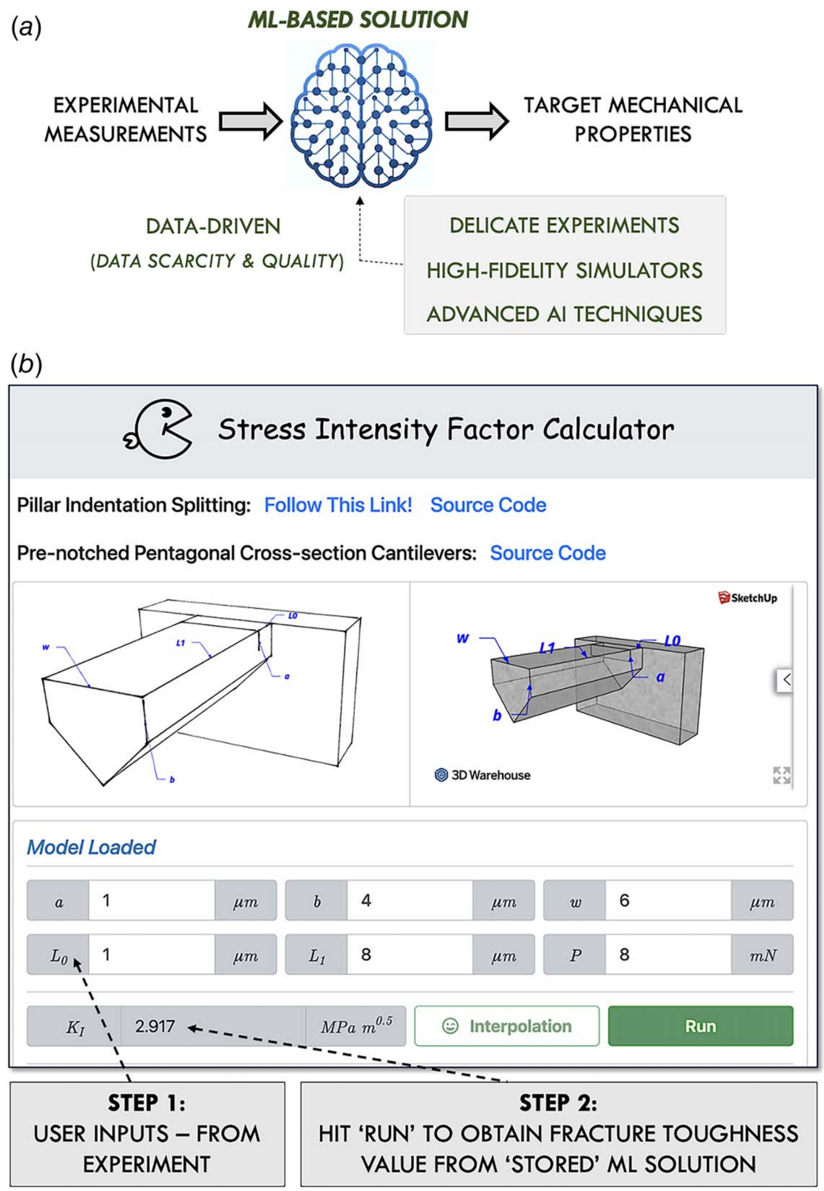

Fig. 3 **(*a*) Establishing a link between experimental measurements and the mechanical properties of interest is challenging for specimens with non-trivial shapes and sizes. We recently proposed that such correlations can be captured using machine learning solutions [26–28]. (*b*) The ML solutions are easily deployable, setting the scene for collaborative efforts on developing and standardizing new mechanical testing instruments and methods for sustainable materials and structures.**

data (Fig. 3(*a*)). However, developing ML-based solutions is data-intensive. Data scarcity is a common challenge that raises reliability concerns. Although assessing the accuracy of ML-based solutions becomes difficult without sufficient data, it is highly recommended to incorporate rigorous accuracy assessment techniques, even with limited data. Advanced ML techniques [27,42], such as active learning, have been introduced to improve the efficiency of data usage. Another challenge in establishing accurate ML-based solutions is data quality. It is essential to eliminate any systematic bias in the training data. Accurate ML-based solutions derived from sufficient amounts of quality data rely on the combination of experimental and simulation approaches [26–28]. Finally, ML-based solutions can be effectively shared in open-standard file formats, along with detailed instructions for their application, therefore facilitating their widespread implementation by the community. Our current efforts include constructing an open-access platform that allows everyone to upload, share, deploy, and revise their own solutions (Fig. 3(*b*)) [26]. Another scenario involves data analysis and interpretation to be directly conducted on a Cloud computing service, where data are processed using advanced AI algorithms, and the results are then sent back to the users. In such scenarios, the local "user" only needs to setup the experiments. The data could be processed centrally, and new experiments suggested, with all computational tasks performed on the Cloud server, thereby offloading the local user's processing and analysis burdens. Such platforms set the scene for collaborative efforts on developing and standardizing new mechanical testing instruments and methods for sustainable materials and structures.

3 The Way Toward Sustainable Materials and Structures

In line with the UN sustainable development goals [1], there is a global push toward circular economy practices for manufacturing products from sustainably sourced materials and decentralizing supply chains. A key aspect to achieve such efforts is the development of open-access pathways allowing for local communities and individuals to engage in mechanical testing, without requiring significant capital investments, licenses to use proprietary software or specialized expertise [43–45]. Facilitating the use of testing instruments though open-access practices could enable the wider adoption of multiscale mechanical testing of heterogeneous renewable feedstocks at the local level (Fig. 4).

However, existing open-access efforts for low-cost mechanical testing solutions face significant challenges, including labor-intensive calibration procedures, poor hardware reliability under different testing conditions, and skill-intensive interpretation of collected data. Fortunately, recent technological advances in the fields of engineering automation and AI can be leveraged to overcome these challenges. AI can be employed in democratizing mechanical testing by reducing human intervention, expediting verification efforts, and contributing to the iterative design of new instruments and methods. AI frameworks, such as active learning, can optimize experimental designs, enhance experimental success rates, and facilitate high-throughput mechanical characterization of heterogeneous materials. In addition, ML-based data interpretation solutions can enable accurate correlation between experimental data and material properties yet requiring sufficient amounts of quality data. Apart from the potential contribution of existing AI frameworks, ongoing AI research and development efforts concerning autonomous design of experiments [46], self-calibrating hardware [47], and multimodal "Text-to-X" generative AI platforms (e.g., Text-to-CAD [48]) could further enhance the implementation of open-access, low-cost and easy-to-use mechanical testing solutions.

Developments for democratizing mechanical testing are expected to be closely intertwined with advancements in the field of mechanics of materials. The variability of the mechanical properties of sustainable materials poses complex modeling challenges. The mechanics community is called to develop modeling frameworks that will incorporate stochasticity for the accurate understanding and prediction of the mechanical behavior of such materials [49]. Significant research efforts need to be undertaken for proposing new deformation models and failure criteria for these highly heterogeneous material systems, using experimental data collected across multiple scales [50], from nano to the continuum scale, and multiple, multi-fidelity sources (e.g., photoelasticity to digital image correlation tests [13–15,25]). Furthermore, it will be critical to obtain easy-to-deploy [51], uncertainty-aware predictive surrogate models, and risk-assessment frameworks based on multiscale

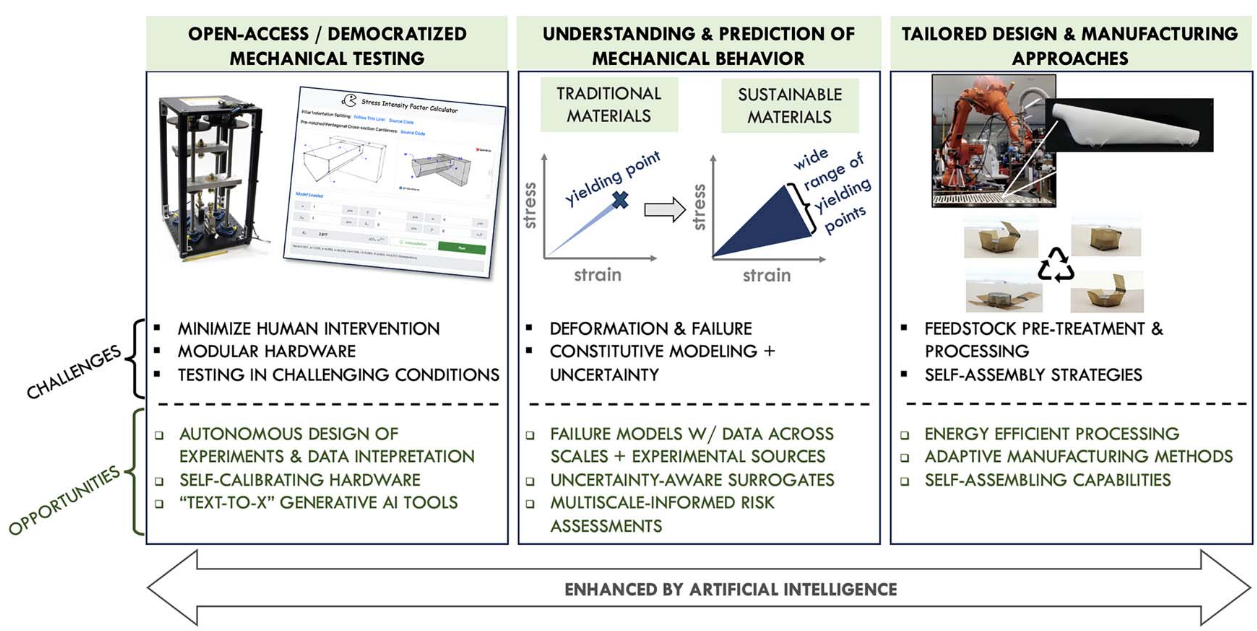

Fig. 4 Enabling the wider adoption of sustainable materials needs democratized mechanical testing [26–28], new mechanics of materials knowledge [13–15,25,50], and tailored design [7–9] and manufacturing approaches [4,11,49]. AI can help overcome existing challenges, e.g., enhancing the predictive accuracy and efficiency of mechanical testing, for deriving uncertainty-aware constitutive laws and for developing data-driven manufacturing models.

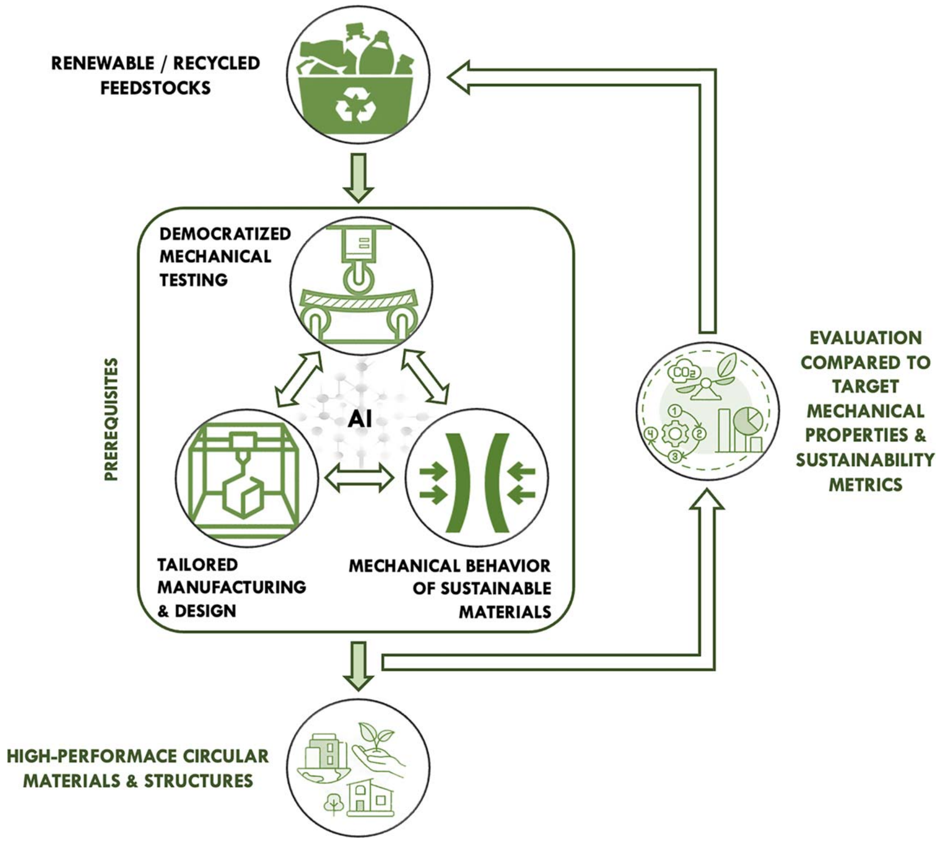

Fig. 5 A proposed closed-loop workflow of how democratized mechanical testing, mechanics of materials and manufacturing research integrated with sustainability metrics can enable the circular use of materials and structures

material responses, while minimizing the amount of data needed. Such advanced predictive capabilities would be essential for designing structures that are both environmentally friendly and mechanically robust.

Lastly, new manufacturing platforms tailored for heterogeneous sustainable feedstocks need to be developed. Traditional manufacturing equipment is designed for homogeneous feedstocks of consistent properties and predictable behavior under standard processing conditions, in order for the developed products to meet the stringent quality criteria demanded by downstream industries. However, bio-based materials may require varying processing temperatures, since seasonality and regionality might affect their melting points or humidity contents [10]. To enable manufacturing of sustainable feedstocks that exhibit stochastic properties and behaviors, adaptive, data-driven manufacturing models able to predict performance and facilitate processing refinements "on-the-fly" need to be developed [49,52]. In addition, specialized pre-treatment approaches are necessary to improve the manufacturability of specific sustainable feedstocks [11]. Developing and optimizing suitable pre-treatment technologies would be critical to enable scalable and energy-efficient manufacturing of sustainable materials. Finally, bioinspired design methodologies, such as self-assembling [53–55] and morphogenesis [56], that have been explored in the recent decades within the mechanics community may assist in accommodating for discrepancies in the feedstock, by carefully controlling self-assembly units and assembly conditions (e.g., temperature, pH [57,58]). These approaches could also facilitate local manufacturing and assembly of sustainably sourced products. However, detailed understanding of the fatigue behavior of heterogeneous sustainable feedstocks will be required to assess their self-assembly capabilities [59,60].

Therefore, to enable circular and local production from sustainable feedstocks, democratized mechanical testing guided by AI is key and goes hand in hand with the generation of new mechanics knowledge as well as the development of tailored and dynamic manufacturing processes. To ensure the overall sustainability and successful implementation of such an approach in practice, it will be necessary to establish relevant metrics and integrate sustainability assessments, e.g., life cycle analysis, from the early stages of research and development processes, to quantify environmental impacts, economic viability, and social implications and identifying areas for improvement (Fig. 5) [61,62].

Acknowledgment

CEA acknowledges support from the National Science Foundation (NSF) CAREER Award [CMMI-2338508].

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

No data, models, or code were generated or used for this paper.

References

[1] Ellen MacArthur Foundation, 2021, "Completing the Picture: How the Circular Economy Tackles Climate Change," https://www.ellenmacarthurfoundation.org/completing-the-picture, Accessed August 7, 2024.

[2] Ashby, M. F., 2012, *Materials and the Environment: Eco-informed Material Choice*, Elsevier, New York.

[3] Board, The Editorial, 2015, "What the Paris Climate Meeting Must Do." *The New York Times*. www.nytimes.com/2015/11/29/opinion/sunday/what-the-paris-climate-meeting-must-do.html

[4] Fernandez, J. G., and Dritsas, S., 2020, "The Biomaterial Age: The Transition Toward a More Sustainable Society Will Be Determined by Advances in Controlling Biological Processes," Matter, **2**(6), pp. 1352–1355.

[5] Oxman, N., 2011, "Variable Property Rapid Prototyping: Inspired by Nature, Where Form Is Characterized by Heterogeneous Compositions, the Paper Presents a Novel Approach to Layered Manufacturing Entitled Variable Property Rapid Prototyping," Virtual Phys. Prototyp., **6**(1), pp. 3–31.
[6] Ben Amor, I., Klinkova, O., Baklouti, M., Elleuch, R., and Tawfiq, I., 2023, "Mechanical Recycling and Its Effects on the Physical and Mechanical Properties of Polyamides," Polymers, **15**(23), p. 4561.
[7] Samir, A., Ashour, F. H., Hakim, A. A., and Bassyouni, M., 2022, "Recent Advances in Biodegradable Polymers for Sustainable Applications," NPJ Mater. Degrad., **6**(1), p. 68.
[8] Kumar, R., Sadeghi, K., Jang, J., and Seo, J., 2023, "Mechanical, Chemical, and Bio-recycling of Biodegradable Plastics: A Review," Sci. Total Environ., **882**, p. 163446.
[9] Forest Products Laboratory, 2021, *Wood Handbook—Wood as an Engineering Material*, General Technical Report FPL-GTR-282, U.S. Department of Agriculture, Forest Service, Forest Products Laboratory, Madison, WI, p. 543.
[10] Thoden van Velzen, E. U., Chu, S., Alvarado Chacon, F., Brouwer, M. T., and Molenveld, K., 2021, "The Impact of Impurities on the Mechanical Properties of Recycled Polyethylene," Packag. Technol. Sci., **34**(4), pp. 219–228.
[11] Mohanty, A. K., Vivekanandhan, S., Pin, J. M., and Misra, M., 2018, "Composites From Renewable and Sustainable Resources: Challenges and Innovations," Science, **362**(6414), pp. 536–542.
[12] Zhu, X. K., and Joyce, J. A., 2012, "Review of Fracture Toughness (G, K, J, CTOD, CTOA) Testing and Standardization," Eng. Fract. Mech., **85**, pp. 1–46.
[13] Athanasiou, C. E., 2018, "Non-contact Femtosecond Laser-Based Methods for Investigating Glass Mechanics at Small Scales," Ph.D. dissertation, Ecole Polytechnique Fédérale de Lausanne, Lausanne.
[14] Athanasiou, C. E., and Bellouard, Y., 2015, "A Monolithic Micro-tensile Tester for Investigating Silicon Dioxide Polymorph Micromechanics, Fabricated and Operated Using a Femtosecond Laser," Micromachines, **6**(9), pp. 1365–1386.
[15] Athanasiou, C. E., Hongler, M. O., and Bellouard, Y., 2017, "Unraveling Brittle-Fracture Statistics From Intermittent Patterns Formed During Femtosecond Laser Exposure," Phys. Rev. Appl., **8**(5), p. 054013.
[16] Johnson, M. W., 2010, *Seizing the White Space: Business Model Innovation for Growth and Renewal*, Harvard Business Press, Boston, MA.
[17] Lund, J. R., and Byrne, J. P., 2001, "Leonardo Da Vinci's Tensile Strength Tests: Implications for the Discovery of Engineering Mechanics," Civil Eng. Syst., **18**(3), pp. 243–250.
[18] Zhou, Y., Zhang, X., Yang, M., Pan, Y., Du, Z., Blanchet, J., Suo, Z., and Lu, T., 2022, "High-Throughput Experiments for Rare-Event Rupture of Materials," Matter, **5**(2), pp. 654–665.
[19] Amend, J. R. Jr, and Lipson, H., 2011, "FreeLoader: An Open Source Universal Testing Machine for High-Throughput Experimentation," IDETC-CIE, Washington, DC, Aug. 28–31, Vol. 54839, pp. 685–693.
[20] Steuben, J. C., Iliopoulos, A. P., and Michopoulos, J. G., 2018, "Open Uniaxial Test Machine (OpenUTM): Part 1—A Low-Cost Electrohydraulic Test Frame for Additive Manufacturing Part Qualification," IDETC-CIE, Quebec City, Quebec, Canada, Aug. 26–29, Vol. 51722, p. V01AT02A047.
[21] Hinge, M., Johnson, J. A., and Henriksen, M. L., 2021, "A Low-Cost Tabletop Tensile Tester With Optical Extensometer," Mater. Adv., **2**(19), pp. 6339–6343.
[22] Summey, L., Zhang, J., Landauer, A., Sergay, J., Yang, J., Daul, A., Tao, J., Park, J., and Franck, C., 2023, "Open Source, In-Situ, Intermediate Strain Rate Tensile Impact Device for Soft Materials and Cell Culture Systems," Exp. Mech., **63**(9), pp. 1445–1460.
[23] Nazir, S. I., Athanasiou, C. E., and Bellouard, Y., 2022, "On the Behavior of Uniaxial Static Stress Loaded Micro-scale Fused Silica Beams at Room Temperature," J. Non-Cryst. Solids, **14**, p. 100083.
[24] Sugerman, G. P., and Rausch, M. K., 2021, "Teaching Material Testing and Characterization With an Open, Accessible, and Affordable Mechanical Test Device," Biomed. Eng. Educ., **2**(1), pp. 1–6.
[25] Athanasiou, C. E., Fincher, C. D., Gilgenbach, C., Gao, H., Carter, W. C., Chiang, Y. M., and Sheldon, B. W., 2024, "*Operando* Measurements of Dendrite-Induced Stresses in Ceramic Electrolytes Using Photoelasticity," Matter, **7**(1), pp. 95–106.
[26] Liu, X., Athanasiou, C. E., Padture, N. P., Sheldon, B. W., and Gao, H., 2020, "A Machine Learning Approach to Fracture Mechanics Problems," Acta Mater., **190**, pp. 105–112.
[27] Liu, X., Athanasiou, C. E., Padture, N. P., Sheldon, B. W., and Gao, H., 2021, "Knowledge Extraction and Transfer in Data-Driven Fracture Mechanics," Proc. Natl. Acad. Sci. USA, **118**(23), p. e2104765118.
[28] Athanasiou, C. E., Liu, X., Zhang, B., Cai, T., Ramirez, C., Padture, N. P., Lou, J., Sheldon, B. W., and Gao, H., 2023, "Integrated Simulation, Machine Learning, and Experimental Approach to Characterizing Fracture Instability in Indentation Pillar-Splitting of Materials," J. Mech. Phys. Solids, **170**, p. 105092.
[29] Lu, L., Dao, M., Kumar, P., Ramamurty, U., Karniadakis, G. E., and Suresh, S., 2020, "Extraction of Mechanical Properties of Materials Through Deep Learning From Instrumented Indentation," Proc. Natl. Acad. Sci. USA, **117**(13), pp. 7052–7062.
[30] Jin, H., Jiao, T., Clifton, R. J., and Kim, K. S., 2022, "Dynamic Fracture of a Bicontinuously Nanostructured Copolymer: A Deep-Learning Analysis of Big-Data-Generating Experiment," J. Mech. Phys. Solids, **164**, p. 104898.
[31] Brodnik, N. R., Carton, S., Muir, C., Ghosh, S., Downey, D., Echlin, M. P., Pollock, T. M., and Daly, S., 2023, "Perspective: Large Language Models in Applied Mechanics," ASME J. Appl. Mech., **90**(10), p. 101008.
[32] Gianola, D. S., della Ventura, N. M., Balbus, G. H., Ziemke, P., Echlin, M. P., and Begley, M. R., 2023, "Advances and Opportunities in High-Throughput Small-Scale Mechanical Testing," Curr. Opin. Solid State Mater. Sci., **27**(4), p. 101090.
[33] Bessa, M. A., Bostanabad, R., Liu, Z., Hu, A., Apley, D. W., Brinson, C., Chen, W., and Liu, W. K., 2017, "A Framework for Data-Driven Analysis of Materials Under Uncertainty: Countering the Curse of Dimensionality," Comput. Methods Appl. Mech. Eng., **320**, pp. 633–667.
[34] Niu, S., Zhang, E., Bazilevs, Y., and Srivastava, V., 2023, "Modeling Finite-Strain Plasticity Using Physics-Informed Neural Network and Assessment of the Network Performance," J. Mech. Phys. Solids, **172**, p. 105177.
[35] Wang, K., and Sun, W., 2019, "Meta-Modeling Game for Deriving Theory-Consistent, Microstructure-Based Traction–Separation Laws Via Deep Reinforcement Learning," Comput. Methods Appl. Mech. Eng., **346**, pp. 216–241.
[36] Guo, K., Yang, Z., Yu, C. H., and Buehler, M. J., 2021, "Artificial Intelligence and Machine Learning in Design of Mechanical Materials," Mater. Horizons, **8**(4), pp. 1153–1172.
[37] Jin, H., Zhang, E., and Espinosa, H. D., 2023, "Recent Advances and Applications of Machine Learning in Experimental Solid Mechanics: A Review," ASME Appl. Mech. Rev., **75**(6), p. 061001.
[38] Flaschel, M., Kumar, S., and De Lorenzis, L., 2021, "Unsupervised Discovery of Interpretable Hyperelastic Constitutive Laws," Comput. Methods Appl. Mech. Eng., **381**, p. 113852.
[39] Kumar, S., and Kochmann, D. M., 2022, "What Machine Learning Can Do for Computational Solid Mechanics," *Current Trends and Open Problems in Computational Mechanics*, F. Aldakheel, B. Hudobivnik, M. Soleimani, H. Wessels, C. Weißenfels, and M. Marino, eds., Springer International Publishing, Cham, Switzerland, pp. 275–285.
[40] Karapiperis, K., Stainier, L., Ortiz, M., and Andrade, J. E., 2021, "Data-Driven Multiscale Modeling in Mechanics," J. Mech. Phys. Solids, **147**, p. 104239.
[41] Trask, N., Martinez, C., Lee, K., and Boyce, B., 2022, "Unsupervised Physics-Informed Disentanglement of Multimodal Data for High-Throughput Scientific Discovery," arXiv:2202.03242.
[42] Zhu, F., Leng, J., Jiang, J. W., Chang, T., Zhang, T., and Gao, H., 2022, "Thermal-Fluctuation Gradient Induced Tangential Entropic Forces in Layered Two-Dimensional Materials," J. Mech. Phys. Solids, **163**, p. 104871.
[43] Gershenfeld, N., 2012, "How to Make Almost Anything: The Digital Fabrication Revolution," Foreign Aff., **91**(6), p. 43.
[44] Cutcher-Gershenfeld, J., Gershenfeld, A., and Gershenfeld, N., 2018, "Digital Fabrication and the Future of Work," Perspect. Work, **22**, pp. 9–14.
[45] Camara, W. D., Choquette, S., Delak, K., Hanisch, R., Long, B., Phillips, M., Ragland, J. M., and Rimmer, C., 2023, "DIGITAL NIST: An Examination of the Obstacles and Opportunities in the Digital Transformation of NIST's Reference Materials," Acta IMEKO, **12**(1), p. 21014.
[46] Szymanski, N. J., Zeng, Y., Huo, H., Bartel, C. J., Kim, H., and Ceder, G., 2021, "Toward Autonomous Design and Synthesis of Novel Inorganic Materials," Mater. Horizons, **8**(8), pp. 2169–2198.
[47] Khan, O., and Kundu, S., 2009, "A Self-adaptive System Architecture to Address Transistor Aging," Design, Automation & Test in Europe Conference & Exhibition, Nice, France, Apr. 20, pp. 81–86.
[48] "Zoo text-to-CAD UI," https://text-to-cad.zoo.dev/. Accessed July 6, 2024.
[49] Athanasiou, C., Deng, B., and Hassen, A. A., 2024, "Integrating Experiments, Simulations, and Artificial Intelligence to Accelerate the Discovery of High-Performance Green Composites," AIAA SCITECH 2024 Forum, Orlando, FL, Jan. 8–12, p. 0041.
[50] Dekhovich, A., Turan, O. T., Yi, J., and Bessa, M. A., 2023, "Cooperative Data-Driven Modeling," Comput. Methods Appl. Mech. Eng., **417**, p. 116432.
[51] Yi, R., Georgiou, D., Liu, X., and Athanasiou, C. E., 2024, "Mechanics-Informed, Model-Free Symbolic Regression Framework for Solving Fracture Problems" (submitted).
[52] Jin, Z., Zhang, Z., and Gu, G. X., 2019, "Autonomous In-Situ Correction of Fused Deposition Modeling Printers Using Computer Vision and Deep Learning," Manuf. Lett., **22**, pp. 11–15.
[53] Jin, H., and Espinosa, H. D., 2024, "Mechanical Metamaterials Fabricated From Self-assembly: A Perspective," ASME J. Appl. Mech., **91**(4), p. 040801.
[54] Zhang, X., Vyatskikh, A., Gao, H., Greer, J. R., and Li, X., 2019, "Lightweight, Flaw-Tolerant, and Ultrastrong Nanoarchitected Carbon," Proc. Natl. Acad. Sci. USA, **116**(14), pp. 6665–6672.
[55] Zhao, Z., Hwang, Y., Yang, Y., Fan, T., Song, J., Suresh, S., and Cho, N. J., 2020, "Actuation and Locomotion Driven by Moisture in Paper Made With Natural Pollen," Proc. Natl. Acad. Sci. USA, **117**(16), pp. 8711–8718.
[56] Zhang, H., and Hu, Y., 2023, "A Statistical-Chain-Based Theory for Dynamic Living Polymeric Gels With Concurrent Diffusion, Chain Remodeling Reactions and Deformation," J. Mech. Phys. Solids, **172**, p. 105155.
[57] Fan, T. F., Park, S., Shi, Q., Zhang, X., Liu, Q., Song, Y., Chin, H., et al., 2020, "Transformation of Hard Pollen Into Soft Matter," Nat. Commun., **11**(1), p. 1449.
[58] Zhao, Z., Kumar, J., Hwang, Y., Deng, J., Ibrahim, M. S. B., Huang, C., Suresh, S., and Cho, N. J., 2021, "Digital Printing of Shape-Morphing Natural Materials," Proc. Natl. Acad. Sci. USA, **118**(43), p. e2113715118.
[59] Carlson, R. L., and Kardomateas, G. A., 1995, *Introduction to Fatigue in Metals and Composites*, Springer Science & Business Media, Dordrecht, Netherlands.
[60] Suresh, S., 1998, *Fatigue of Materials*, Cambridge University Press, Cambridge, UK.
[61] Stathatou, P. M., Corbin, L., Meredith, J. C., and Garmulewicz, A., 2023, "Biomaterials and Regenerative Agriculture: A Methodological Framework to Enable Circular Transitions," Sustainability, **15**(19), p. 14306.
[62] Realff, M. J., 2022, "When Is "Net Zero Net Zero?"," J. Adv. Manuf. Process., **4**(3), p. e10135.