My aim and vision: I am committed to advancing my research portfolio through collaboration within and beyond my field, balancing foundational and applied research. My work focuses on developing the theoretical foundations of Causal Neuro-symbolic (Causal NeSy) AI while addressing practical, industry-relevant use cases. Learning from mentors across interdisciplinary domains has shaped my research approach, emphasizing collaboration with researchers and industry partners to tackle real-world challenges. My experience with joint research and industry collaborations positions me to make meaningful contributions to the emerging field of Causal NeSy AI. This multifaceted research aligns with diverse funding opportunities, including NIH and NSF programs such as Career, EAGER, CISE, RISE, CNS, and Smart and Connected Health. These opportunities and prior experience on projects like the NICHD R01 award and NIBIB submissions for pediatric asthma provide a solid foundation to sustain and innovate at the intersection of fundamental and applied science.

Causal Neuro-symbolic AI: The integration of causal AI and neuro-symbolic AI represents a transformative frontier in artificial intelligence, combining their strengths to enhance causal reasoning, decision support, and system ***interpretability***. By embedding causal structures into neuro-symbolic models, these systems become more ***robust***, ***explainable***, and adaptable to changing data, making them ideal for safety-critical applications like healthcare and autonomous driving. Leveraging domain knowledge through knowledge graphs and incorporating ***safety*** constraints as logical rules further boosts reliability and ***ethical alignment***. NeSy AI also addresses ***scalability*** challenges in causal AI, advancing toward general intelligence by integrating causal reasoning with multimodal insights for tasks like causal discovery, strategic planning, and policy evaluation. I am particularly passionate about the Causal NeSy AI framework, which identifies missing causal relations using interventions and counterfactuals for applications such as autonomous scene understanding, healthcare treatment effect estimation, and root cause analysis in manufacturing. These efforts, validated through high-impact publications, demonstrate the real-world potential of this innovative approach.

Current research - Causal Neuro-symbolic AI: (a) Causal ontology and causal knowledge graph- Just as a common language facilitates human communication, a unified representation is essential for merging distinct fields. I have developed a ***causal ontology*** to represent causal relations within a knowledge graph [8]. This ontology enables the translation of causal structures from CBNs into knowledge graphs, enhancing causal reasoning within the Causal NeSy AI framework. Rooted in the foundational concepts of the Causal AI community, including CBNs and do-calculus, this ontology models three critical elements: causal relations, causal event roles, and causal effect weights. It supports RDF[1]-based triples and RDF-star[2] hyper-relation representations, offering enriched contextual information. A ***causal knowledge graph*** can be constructed from observational data and existing domain knowledge by utilizing these representations, enabling more robust and interpretable AI systems [7]. **(b) Causal link prediction:** CBNs are vital in applications like medical diagnosis and root-cause analysis in manufacturing. However, real-world data often contains missing and unmeasured confounders, leading to incomplete CBNs. To address this, I developed Causal Link Prediction (CausalLP) methods, which reframes the problem of finding missing causal links as a knowledge graph completion task [11]. This approach annotates known causal links with causal effect weights to represent their strength and introduces a Markov-based split technique. The Markov-based split is a novel data split technique that utilizes the Markovian property of CBNs to reduce the bias. Evaluations using a causal benchmark dataset show that weighted causal links outperform the baseline by 112.03% in mean reciprocal rank (MRR). Additionally, the Markov-based split reduces data leakage and model bias by 14% (MRR) compared to random splits. **(c) Influence of mediators in causal link prediction:** In causal chains like "A causes B causes C," B acts as a mediator and captures essential contextual information. Traditional knowledge graph link prediction methods cannot handle these mediated relations. To address this gap, I've developed a HyperCausalLP method that incorporates mediators into hyper-relational knowledge graphs to improve link prediction [13]. Evaluations indicate that including knowledge about mediators improves performance by an average of 5.94% in MRR. **(d) Influence of confounders in causal link prediction:** Confounders for a given causal link between cause-effect

[1] https://www.w3.org/RDF/

[2] https://w3c.github.io/rdf-star/

entities can skew causal link predictions, leading to spurious and inaccurate results. To counteract this, I've introduced CausalLP-Back, which uses backdoor path adjustment to eliminate confounder effects [12]. Backdoor paths are non-causal links that connect the cause-entity to the effect-entity through other variables. By removing these paths, CausalLP-Back ensures more accurate causal link predictions. Evaluations demonstrate at least a 30% improvement in MRR and a 16% increase in Hits@K for both non-weighted and weighted causal relations, highlighting the reduction of bias introduced by backdoor paths. *My current research demonstrates the Causal NeSy ability to adopt causal AI concepts such as backdoor path adjustment, causal Markovian property, and causal effect weights in the NeSy framework.*

Application of Causal NeSy AI in real use cases: (1) Causal understanding in autonomous driving: Current autonomous driving systems often rely on observational data and capture correlations rather than causal relationships. To address this issue, I integrated causal reasoning with domain knowledge expressed through a causal knowledge graph [9]. This framework improves decision-making in safety-critical scenarios by enhancing the system's ability to perform counterfactual and intervention reasoning. By combining causal relationships with domain knowledge, autonomous driving systems can better interpret and respond to unobserved scenarios like malfunctions or accidents. This work is done in collaboration with ***Bosch Center for AI***. **(2) Root cause analysis in smart manufacturing:** Root cause analysis is crucial for identifying failures in manufacturing but is often challenged by complex production lines and volumes of data. I applied Causal NeSy AI with causal reasoning to analyze the root cause of failures in smart manufacturing assembly lines [10]. Using data from an industry-grade rocket assembly line, we demonstrate the approach's effectiveness in enhancing fault detection and providing actionable insights to improve production line efficiency and reliability. The work is done in collaboration with new and emerging X technologies (***neXt***) team in manufacturing at the University.

Research dissemination and impact: In addition to technical skills, the nature of my work has also enhanced my academic writing through first-author papers, proposals, and oral communication through various conference presentations. I've also supervised masters and undergraduate students working on the above projects. These experiences have taught me crucial soft skills, such as leadership, acumen, and time management. These skills make me a better researcher. I am ***organizing a workshop*** on my dissertation, Causal NeSy AI, at the Extended Semantic Web Conference (ESWC) 2025 to bring together the growing community of researchers in Causal and NeSy AI. I have also served as a ***reviewer*** for top-tier conferences and journals such as ISWC Semantic Sensor Networks, IEEE International Conference on Fuzzy Systems, The Web Conference, Semantic Web Journal, Journal of Medical Internet Research, Transactions on Fuzzy Systems, and Journal of Web Semantics. I've also received competitive travel grants and ***scholarships*** to attend IEEE International Conference on Healthcare Informatics 2016, IEEE SmartComp 2017, Ohio Conference Women in Conference (OCWiC) 2017 and 2019, ACM Tri-state Women in Computing 2018, CRA-WP conference 2020, AnitaB Grace Hopper Scholar 2020, ISWC 2024, etc. I've effective and productive inter-disciplinary research collaborations with Nationwide Children's Hospital, Columbus, OH; Bassett Medical Center, NY; School of Professional Psychology at the Wright State University; College of Nursing, University of South Carolina; new and emerging X technologies (neXt) Future Factories at McNAIR Aerospace Center, University of South Carolina; Bosch center for AI; Siemens Technology. The research, in collaboration with industry partners, has been filed as ***invention reports*** (3) and subsequent ***patent*** applications (1). Through my teaching experience, which includes delivering **tutorials**, invited talks at the Web Conference and Knowledge Graph Conference (KGC), and **co-instructing courses**, I have honed my ability to extend my research and explore new, pressing research directions. These experiences have equipped me with the skills necessary to pursue and secure ***funding*** from prestigious sources such as NSF, NIH, AFRL, and industry grants. For instance, the following proposals were a follow-up of my work in personalized pediatric asthma care- (1) *kHealth-OA*: A Multisensory Data-enhanced Evidence-based Obesity Management in Children with Asthma, Agency: NIH, Amount: $1.1M (***Lead student contributor***); (2) *InterACT-MI:* A Chatbot-delivered Motivational Interviewing Intervention for Adolescents with Asthma, Agency: NIH NIBIB, Amount: $1.7M (***Lead student contributor***). Also, I am thrilled to contribute to a multi-institute proposal where I proposed a causal model for the dynamic offline-online information exchange and its effect, (3) *MURI*: Developing a Computational Approach for Understanding Information Exchange Network Dynamics, Agency: ARO, Amount: $6.25M.

Broader impact and future research vision: Causal NeSy AI can transform the next generation of AI systems by combining the strengths of neural networks, symbolic reasoning, and causal inference to address critical challenges in artificial intelligence. My research aims to bridge the gap between correlation-based learning and causal understanding, enabling AI systems to operate reliably in dynamic and complex real-world environments. This work contributes to advancing AI as a scientific discipline and its application in critical societal domains.

Short-term research goals (next 2-5 years): (1) Extending Causal NeSy AI models to handle complex real-world scenarios: My immediate focus is refining causal neuro-symbolic models to address more complex and dynamic scenarios. For instance: (1) *Healthcare*: The integration of Causal NeSy AI in healthcare can transform patient care through actionable insights, such as policy estimation for personalized treatment plans and optimizing intervention strategies; (2) *Decision Support Systems*: By enabling counterfactual and intervention reasoning, Causal NeSy AI can enhance decision support systems across industries, offering transparent and reliable recommendations in complex scenarios. **(2) Developing benchmarks for causal reasoning evaluation:** To facilitate progress in the field, I aim to develop standardized benchmarks and datasets for evaluating the causal reasoning capability of Causal NeSy in AI systems. These benchmarks will enable rigorous comparison and validation of different approaches, fostering innovation and collaboration within the research community. **(3) Integrating Causal NeSy AI with reinforcement learning**: I plan to explore the integration of CausalNeSy AI with reinforcement learning, particularly in healthcare applications. For example, leveraging causal reinforcement learning and Causal NeSy AI can optimize intervention policies for chronic conditions, such as asthma, balancing long-term and short-term treatments to improve patient outcomes while providing robust, explainable results.

Longer-term research goals (5+ Years): (1) Creating general-purpose causal reasoning systems: A key long-term goal is the development of general-purpose causal reasoning systems capable of operating across diverse domains, from healthcare and finance to autonomous systems and other industrial applications. **(2) Advancing scientific discovery**: Causal NeSy AI has the potential to revolutionize scientific discovery by enabling hypothesis generation and testing via multiple causal models in domains like drug discovery, climate modeling, and fundamental research. This could accelerate innovation and provide insights that were previously unattainable. **(3) Addressing ethical implications and societal impact**: My research will also explore the ethical and social implications of various economic and social policy changes (i.e., interventions). I aim to ensure that these technologies are deployed responsibly and equitably by addressing issues such as fairness, accountability, and transparency.

Summary and building on current research: My current research provides a solid foundation for my future research goals by integrating causal reasoning with neuro-symbolic systems to enable interpretable, robust, explainable, and actionable AI systems. My work on defining and developing the Causal NeSy AI framework demonstrates the theoretical potential of this research. My contributions to applications in asthma management, industrial metaverse knowledge graphs, autonomous driving, and smart manufacturing demonstrate the practical potential of this research. These experiences provide a robust platform for scaling Causal NeSy AI to new domains and challenges, ensuring its broader impact across society. By advancing the theoretical underpinnings and practical applications of Causal NeSy AI, my research aims to make AI systems safer, more trustworthy, and more impactful across critical domains, contributing meaningfully to AI's development as a tool for the betterment of society. I will seek NSF funding for foundational research (some of which could be interdisciplinary - such as smart manufacturing), NIH funding for collaborative research with health applications, and DOE/DoD funding for interdisciplinary research with applications to energy transition, logistics, transportation, etc. In my current research group, I have also had exposure to large collaborative efforts with budgets ranging from $5M (E.g., NSF Bridges) to $20M (e.g., NSF AI Institutes); thus if the department/college/university is seeking such funding, I will remain eager to be part of larger team efforts.

References

1. Munroe, Randall. "What If?: Serious Scientific Answers to Absurd Hypothetical Questions by." (1986).
2. Gopnik, Alison, Clark Glymour, David M. Sobel, Laura E. Schulz, Tamar Kushnir, and David Danks. "A theory of causal learning in children: causal maps and Bayes nets." Psychological review 111, no. 1 (2004): 3.
3. Sobel, David M., Joshua B. Tenenbaum, and Alison Gopnik. "Children's causal inferences from indirect evidence: Backwards blocking and Bayesian reasoning in preschoolers." Cognitive science 28, no. 3 (2004): 303-333.
4. Marcus, Gary, and Ernest Davis. Rebooting AI: Building artificial intelligence we can trust. Vintage, 2019.
5. Evans, Melbourne G. "Causality and Explanation in the Logic of Aristotle." Philosophy and Phenomenological Research 19, no. 4 (1959): 466-485.
6. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "Causal Neuro-Symbolic AI: A Synergy Between Causality and Neuro-Symbolic Methods." IEEE Intelligent Systems 39, no. 2 (2024).
7. Jaimini, Utkarshani, and Amit Sheth. "CausalKG: Causal Knowledge Graph Explainability using interventional and counterfactual reasoning." IEEE Internet Computing 26, no. 1 (2022): 43-50.
8. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "An Ontology Design Pattern for Representing Causality." In Workshop on Ontology Design and Patterns at International Semantic Web Conference. (2023).
9. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "Causal Knowledge Graph for Scene Understanding in Autonomous Driving." In International Semantic Web Conference. (2024).
10. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "Causal Neuro-Symbolic AI for Root Cause Analysis in Smart Manufacturing." In International Semantic Web Conference. (2024).
11. Jaimini, U., C. Henson, and A. P. Sheth. "Causallp: Learning causal relations with weighted knowledge graph link prediction." arXiv preprint arXiv:2405.02327 (2024).
12. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "Influence of Backdoor Paths on Causal Link Prediction." arXiv preprint arXiv:2410.14680 (2024).
13. Jaimini, Utkarshani, Cory Henson, and Amit Sheth. "HyperCausalLP: Causal Link Prediction using Hyper-Relational Knowledge Graph." arXiv preprint arXiv:2410.14679 (2024).
14. Jaimini, Utkarshani, Tongtao Zhang, Georgia Olympia Brikis, and Amit Sheth. "imetaversekg: Industrial metaverse knowledge graph to promote interoperability in design and engineering applications." IEEE Internet Computing 26, no. 6 (2022): 59-67.
15. Jaimini, Utkarshani, Tongtao Zhang, and Georgia Olympia Brikis. "MetaverseKG: Knowledge Graph for Engineering and Design Application in Industrial Metaverse." In International Semantic Web Conference (2022).
16. Jaimini, Utkarshani, Krishnaprasad Thirunarayan, Maninder Kalra, Robin Dawson, and Amit Sheth. "Personalized Bayesian Inference for Explainable Healthcare Management and Intervention." In 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), pp. 725-731. IEEE, 2024.
17. Jaimini, Utkarshani, and Amit Sheth. "Personalized Digital Phenotype Score, Healthcare Management and Intervention Strategies Using Knowledge Enabled Digital Health Framework for Pediatric Asthma." In Recent Advances in Asthma Research and Treatments. IntechOpen, 2021.
18. Jaimini, Utkarshani, Krishnaprasad Thirunarayan, Maninder Kalra, Revathy Venkataraman, Dipesh Kadariya, and Amit Sheth. "“How Is My Child’s Asthma?” digital phenotype and actionable insights for pediatric asthma." JMIR pediatrics and parenting 1, no. 2 (2018): e11988.