"Knowledge is the object of our inquiry, and men do not think they know a thing till they have grasped the 'why' of it (which is to grasp its primary cause)." Aristotle Physics 194 b 18

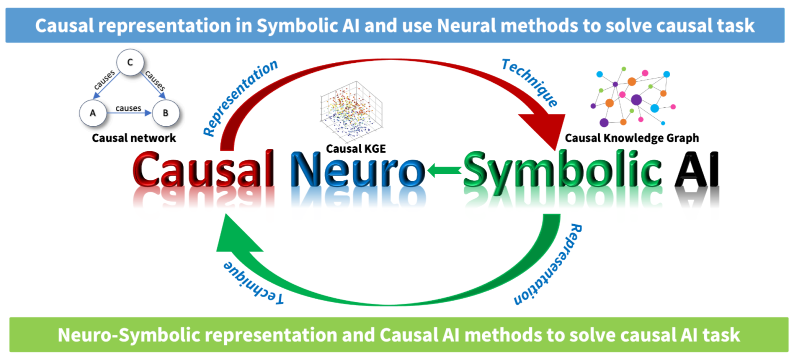
I am driven by curiosity. My research mantra is "Always stay hungry". A desire to satiate the hunger to understand the reason behind the phenomenon in the world motivates me to research causality. The questions of "Why" and “What if?” (i.e., counterfactual) are embodied in every sphere of our life [1]. From an early age, a child adopts a causal view of the world [2,3]. They are curious to learn about the internal workings and reasoning of the world around them. Humans have inherently learned to look at the world through a causal lens. Aristotle, in 300 BC, was the first to talk about causality. Since then, research in causality has significantly evolved from Aristotle to Sewall Wright and Judea Pearl’s do-calculus [5]. In our current era, artificial intelligence (AI) systems must integrate formal representations of space, time, and causality to model the complexities of the world [4] accurately. My research emphasizes embedding causal knowledge into AI systems to enable a human-like understanding of phenomena and situations via a framework called ***Causal Neuro-symbolic (Causal NeSy) AI*** [6]. The ultimate goal of my work is to equip AI systems with an understanding of cause-and-effect relationships—enabling them to comprehend the consequences of their actions and make decisions accordingly. My research demonstrates that incorporating domain knowledge, alongside causal reasoning, significantly enhances the performance of AI systems and their ability to deliver user-centric causal insights.

Current approach and challenges: Current causal modeling techniques primarily rely on Causal Bayesian Networks (CBN). This approach involves either learning the network structure from data using structure-learning algorithms or utilizing a network provided by domain experts. However, *existing learning algorithms applied to experimental or observational data often fail to uncover the true causal structure of the system*. To address this, a "human-in-the-loop" approach is sometimes employed, where domain experts assist by providing initial guidance, such as specifying edges for the algorithm to learn from. In safety-critical domains like healthcare, relying on expert input poses significant challenges. Experts are often overburdened, with limited time and resources for tasks like analyzing observational data. This makes it impractical to rely on their input in the modeling process consistently. My research focuses on incorporating domain expertise through human-in-the-loop models or leveraging knowledge embedded in knowledge graphs to *develop user-explainable causal models and systems*. I have applied this approach in pediatric healthcare projects, autonomous driving, and smart manufacturing.

My aim and vision: I am deeply committed to advancing and strengthening my research portfolio through collaborative efforts within and beyond my field. My work is characterized by a balance of foundational and applied research. One dimension of my research is dedicated to advancing the theoretical underpinnings of Causal NeSy AI. At the same time, another focuses on addressing practical use cases with immediate relevance and impact on the industry. I have been fortunate to learn from and work alongside mentors from diverse, interdisciplinary domains, which have profoundly shaped my research approach. I aim to foster collaborations with researchers across related fields and to engage actively with industry partners to better understand and address real-world challenges. My previous experience working on joint research projects and collaborating with industry has provided me the foundation to pursue these goals effectively. I am excited about the opportunity to contribute to, shape, and make a meaningful impact in the emerging field of Causal NeSy AI. The multifaceted nature of this research aligns well with a broad spectrum of funding opportunities, including NIH and NSF Career grants, NSF EAGER, NSF CISE (Directorate for Computer and Information Science and Engineering), NSF RISE (Division of Research, Innovation, Synergies, and Education), NSF CNS (Division of Computer and Network Systems), and initiatives such as NSF Smart and Connected Health (SCH). Opportunities to seek NIH funds come through collaboration with clinical and biomedical researchers (as was the case with R01 award from NICHD on pediatric asthma I worked on early in my research and two additional R01 NICHD and NIBIB submissions with my advisor’s collaborators). These avenues provide an excellent framework to support and sustain my research ambitions while fostering innovation at the intersection of fundamental and applied science.

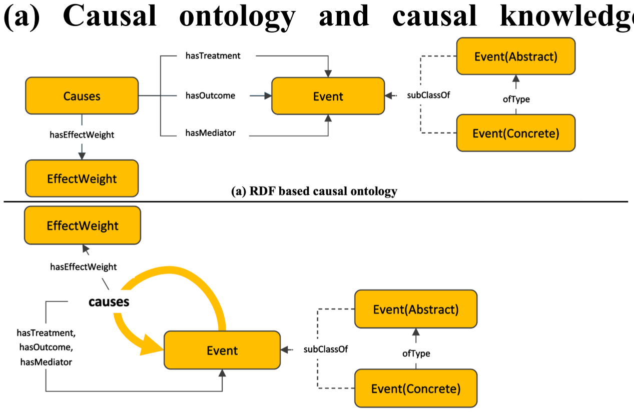
Causal Neuro-symbolic AI

The integration of causal AI and neuro-symbolic AI represents a transformative and promising frontier in artificial intelligence research. This synergy harnesses the complementary strengths of both paradigms, enhancing causal reasoning and learning capabilities while significantly improving decision support systems. The ongoing progress in this field is evident as it paves the way for developing more accurate, interpretable, and intelligent models that elevate AI systems' causal understanding and reasoning abilities. By embedding causal representation into neuro-symbolic AI models, these systems improve reasoning capabilities and reinforce ***robustness*** and ***explainability*** by focusing on underlying causal structures. Such systems remain effective even as data conditions evolve, making them well-suited for real-world applications. It contributes to making AI systems accountable and thus suitable for deployment in safety-critical applications such as autonomous driving and healthcare. The causal representation is further ***grounded*** in domain knowledge embedded within knowledge graphs, enhancing system ***reliability***. The inclusion of causality in symbolic representation provides a mechanism to incorporate ***safety*** constraints as logical rules, fostering ***trust*** in critical domains such as healthcare and finance. It ensures that AI systems are interpretable and aligned with ***ethical*** principles. Neuro-symbolic AI methods offer ***scalable*** solutions compared to existing causal AI methods, which are limited in scalability beyond a few hundred parameters. Beyond addressing immediate challenges, this integration advances AI toward general intelligence by emulating human cognitive processes. It combines causal reasoning with multimodal insights to tackle complex problems such as causal discovery, strategic planning, and policy evaluation. I am particularly passionate about the Causal NeSy AI framework, which offers a robust platform for learning missing causal relations in data. It leverages interventions and counterfactuals for autonomous scene understanding, treatment effect estimation in healthcare, and root cause analysis in smart manufacturing. These projects serve as proof-of-concept for deploying such technology in real-world scenarios and have gained recognition through publications at prestigious journals and conferences.



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) RDF-star based causal ontology

Figure: Causal Ontology for representing causal concepts from causal Bayesian network into knowledge graph

(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

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

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

incomplete CBNs. To address this, I developed methods for Causal Link Prediction (CausalLP), 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 method called HyperCausalLP that incorporates mediators into hyper-relational knowledge graphs for improving link prediction [13]. Evaluations indicate that including knowledge about mediators improves performance by an average of 5.94% in MRR.

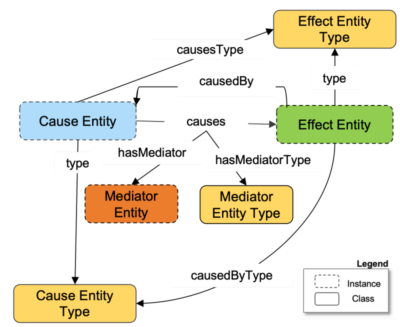


Figure: Hyper-relational knowledge graph with mediator as hyper-relations

(d) Influence of confounders in causal link prediction: Confounders for a given causal link between cause-effect 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:

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***.

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 a smart manufacturing assembly line [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. This work is done in collaboration with new and emerging X technologies (***neXt***) Future Factories at ***McNAIR Aerospace Center, University of South Carolina.***

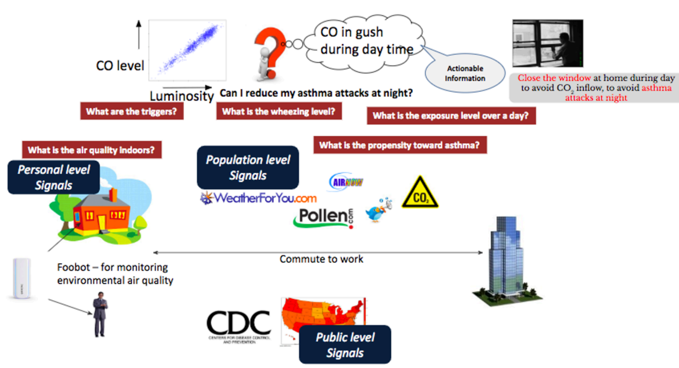


Figure: kHealth, Decision support scenario for doctors and patients

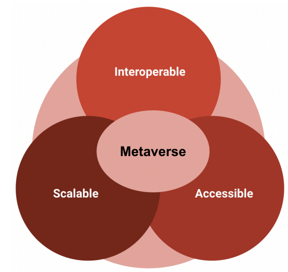
Other key research contributions

During my PhD, while focusing on Causal NeSy AI, I've engaged in several other interdisciplinary projects that have broadened my research experience. Here are some key contributions:

Personalized asthma care: As the lead student coordinator for the NIH-funded project "kHealth: Personalized Disease Management for Pediatric Asthma Patients," I collaborated with clinicians at ***Dayton***

Children's Hospital to recruit 150 pediatric asthma patients and led a team of 5 (graduate and undergraduate) students in project development. We integrated mobile computing, IoT sensors, and domain knowledge to enhance disease management. My research focused on providing actionable, personalized information through computational models like Bayesian inference [16]. I developed a Digital Phenotype Score and Health Coefficient to quantify digital phenotypes from sensor data, offering real-time insights beyond traditional Asthma Control Test scores. This enabled early assessments and interventions, improving long-term outcomes for pediatric asthma patients [17, 18].

Industrial metaverse knowledge graph: During my summer internship with ***Siemens***, I contributed to the company's efforts in the industrial metaverse by developing the first Industrial Metaverse Knowledge Graph (iMetaverseKG) [14, 15]. This work aimed to enhance interoperability across industrial applications using Knowledge Graph technologies. The iMetaverseKG was developed with a use case from design and engineering, demonstrating how these technologies can integrate diverse industrial processes for more cohesive workflows. This research provides a framework for advancing practical applications of the industrial metaverse, promoting more connected and intelligent ecosystems.



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 holds the potential to 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)

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.

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.

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)

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.

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.

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.

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