In DARPA's view on three phases of AI, following hand-crafted knowledge and statistical learning, the third phase is contextual adaptation. This phase seeks to use the best of both symbolic AI and statistical AI and is often referred to as neuro-symbolic AI. Knowledge representation as expert system rules or using frames and a variety of logics played a key role in capturing explicit knowledge during the hay days of AI in the past century. Such knowledge, aligned with planning and reasoning, is part of what we refer to as Symbolic AI. My research is about a class of neuro-symbolic AI in which explicit knowledge plays a central role. After initial hesitancy about the scalability of the knowledge creation process, the last decade has seen significant growth in developing and applying knowledge, usually in the form of knowledge graphs (KG). Examples range from the use of DBPedia in IBM's Watson to Google Knowledge Graph in Google Semantic Search, and the application of ProteinBank in AlphaFold, recognized by many as the most significant AI breakthrough, as well as numerous domain-specific knowledge have been applied in improving AI methods in diverse domains such as medicine and healthcare, finance, manufacturing, and defense. I will specifically look at my endeavor to support human-like intelligence, our desire for AI systems to interact with humans naturally, and our need to explain the path and reasons for AI systems' workings. Nevertheless, the variety of knowledge needed to support understanding and intelligence is varied and complex. My dissertation thesis, titled **Knowledge-infused Mining and Learning (KiML)** advances the state of the art in five research thrust areas: **(1)** Recommender systems (*recsys*) **[ICHI, DSAA, CIKM], (2)** learning to rank (*l2r*) algorithms **[AAAI, WWW], (3)** summarization (*summ*) **[JMIR], (4)** conversational AI (*convAI*) **[AAAI-22, ACL*],** and **(5)** Computational Social Data Science **[ICHI, CSCW, AMIA, FM*]**. An important corollary of my research is that it addresses one of the most important hurdles in the wider acceptance of AI: 91% of the companies surveyed indicated the need to have explainable AI, which forms a pertinent component in KiML. By using KiML, I contribute towards this timely need for Interpretable and Explainable Machine Learning. I have demonstrated its benefits in various multidisciplinary research applications, including healthcare, cyber social threats, crisis management, and digital security. In this statement, I emphasize the importance of KiML in **semantic social computing** through applications in **mental healthcare, time-evolving events in crisis, conversational information seeking, and digital security**, along with its utility in supporting explainability in AI. Further, I will enumerate my plans for future research in core AI and its applications to diverse fields.

Brief history and Challenges

Hand-crafted methods in AI, such UCB Hearst Pattern (1992), NYU Proteus (1997) were effective in learning underlying patterns. With supervised learning methods, AI drifted towards large scale data acquisition and annotations, ignoring the explicit knowledge implicitly embedded in data preparation. Weakly and distantly supervised learning methods showed the importance of including explicit knowledge, but still relies on knowledge's statistical representation.

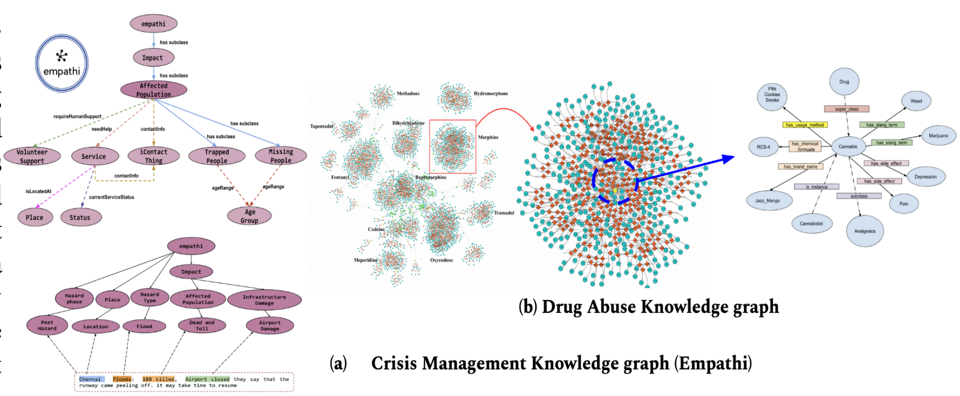

Figure 1: Domain-specific knowledge graphs for Epidemiology and Crisis Management Research on complex social media data

Particularly, fields like *recsys, l2r), summ* (NLP/NLU[1]), and *convAI* (NLP/NLU), revealed drawbacks of existing statistical AI methods in achieving acceptability and adoption by communities of experts. For instance, Han et al. enumerated the reasons for under-performance of content+collaborative *recsys* in healthcare, mostly directed towards the ignorance of ground-truth guidelines (or rules), such as ICD-10[2] and UMLS[3] hierarchy, and conceptual features explaining one's health conditions. In *l2r,* state-of-the-art statistical AI methods heavily rely on the co-occurrences of pairs of words. As a consequence, it is difficult to rank documents/contents when the query is about an emerging topic with minimal co-occurrences (e.g. long tail entities **[WWW 2019])**. Moreover any statistical AI algorithm functions on latent dimensions making ranking of documents/contents hard to explain. Algorithms in *summ* have a hard time in modeling knowledge constraints causing the end result to significantly differ from useful and actionable summaries **[JMIR 2021]**. In *convAI*, an intrinsic task of any statistical AI algorithm (preferably deep learning) is to understand user behavior during

[1] Natural Language Processing (NLP)/Natural Language Understanding (NLU)

[2] International Classification of Diseases (ICD)

[3] Unified Medical Language System (UMLS)

interactive search and later improve accuracy during search sessions. Research *convAI* has been hampered by a lack of datasets that involve process knowledge, an approach experts follow during any formal conversational setting. Furthermore, algorithms trained on some standard benchmark datasets, such as General Language Understanding and Evaluation (GLUE) become rigid and lack reusability across other domains. These challenges broadly highlight the need of knowledge-intensive datasets and KiML algorithms that provide multi-hop knowledge traversal **[ISWC 2018]**, domain-specific knowledge infusion **[CSCW 2019]**, executable in low-resource domains **[AAAI 2020]**, and support symbolic knowledge integration **[JMIR 2021]**. By developing the KiML paradigm, the dissertation answers the question: **Can incorporation of domain knowledge enhance the performance and explainability of data-intensive learning models?**

KiML paradigm steward knowledge graphs, a machine readable structured representation of knowledge consisting of entities (entity and entity type) and relationships in various forms (e.g., labeled property graphs and RDFs). **Figure 1**, illustrates two knowledge graphs; (a) An *Empathi Ontology*[4] constructed to support emergency responders in identifying crucial events on time-evolving information from social media streams. (b) An *Educational Knowledge graph* constructed from epubs of Amazon books, and other course textbooks to assess a student's learning outcome and suggest ways to improve. These domain-specific knowledge graphs provide necessary information aid for machine learning/deep learning algorithms for domain adaptation and reasoning over the outcomes. There are various ways to incorporate external knowledge which my dissertation categorizes into (a) Shallow Infusion, (b) Semi-Deep Infusion, and (c) Deep Infusion. *Shallow knowledge infusion* contextualizes the training examples with expert knowledge to capture meaningful patterns. Some of the shallow infusion examples include contextual modeling **[CSCW 2019]**, entity normalization **[WWW 2019]** and explainable clustering **[AMIA 2021]**. *Semi-deep knowledge infusion* guides the model's attention in the learning process. It utilizes expert knowledge concepts as weights or constraints to guide an explainable learning process. This strategy falls short in assisting deep learning models adjust the high-level abstractions learnt through multiple layers. *Deep Knowledge Infusion*, combines the stratified representation of knowledge at varying abstraction levels to be transferred in different layers of deep learning models **[AAAIc 2020]**. I present methodological architectures of these strategies in **Figure 2**. This research statement focuses primarily on the utility of KiML algorithms in following applications:

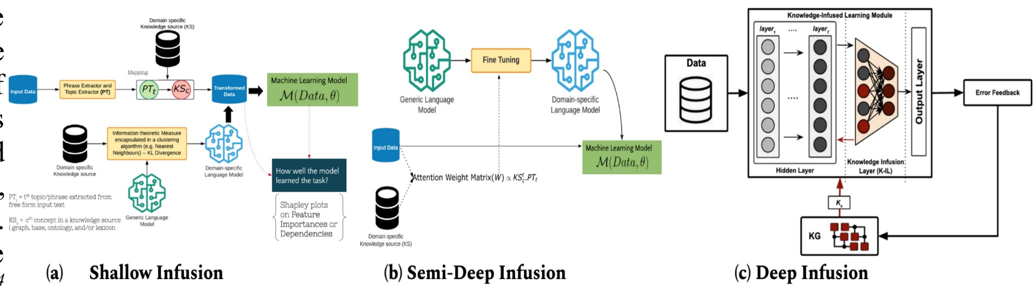

Figure 2: Different architectural variants of Knowledge infused Mining and Learning

(A) ***Domain Adaptation and Inference (recsys):*** Dependence on expert labeling is not only impractical but leads to spurious feature selection and implausible explanations **[WWW 2019]**. To generate semantic labels for unlabeled social media data automatically without expert supervision, I developed a novel semantic encoding and decoding (SEDO) algorithm (semi-deep infusion) that would learn a weight matrix (W) between concepts in unlabeled data and concept classes in knowledge graph (KG). To test the efficiency and reliability of SEDO, I curated natural testbeds in collaboration with psychiatrists in **Wright State Psychiatry**, and **Weill Cornell Medicine**. In comparison with the traditional statistical model, SEDO reduced false alarms by 92%, while achieving 84% annotator agreement. This was the first KG-based zero-shot (problem scenarios with no label data) approach with explainable outcomes **[IC 2019, IC 2020, IC 2021, CIKM 2018]** and has been extended to detect suicide risk from a mix of supportive and at-risk users posting on Reddit **[WWW 2019]**. The testbed has >3400 downloads and has been employed by researchers in the intersection of explainable AI and healthcare. Furthermore, it has opened new research directions in facilitating formation of dynamic peer support groups on social media. A knowledge-infused siamese network was trained and adapted to understand the conversations between support seekers and support providers on Reddit for suitable matching. A natural language inference layer was appended at the end to classify the pair of users as; (a) both are support seekers (entailment), and (b) one is support seeker and other is support provider (contradiction). An illustration in **Figure 3** shows the matching **[ICHI 2021]**. The study received

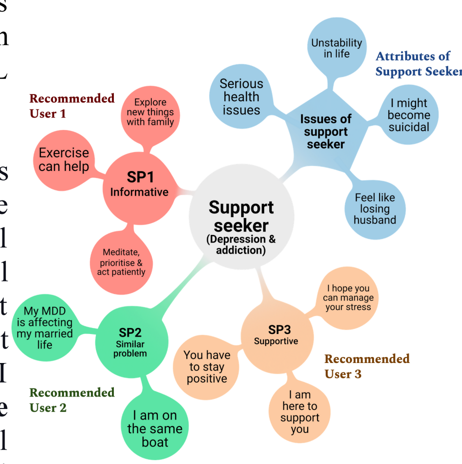

Figure 3: Recommending support providers to support seekers for mental health assistance

[4] https://shekarpour.github.io/empathi.io/

attention from various non-profits in the US, state department on mental health in south carolina, and industry-oriented meetings such as Geekle.us. Prior research at the intersection of social media, explainable AI, and healthcare did not focus on incorporating external knowledge in model learning and anchor into costly human resources for annotation, verification, and validation. The seamless incorporation of clinical expertise and guidelines in computational mental healthcare research is an open research problem that I would be interested in exploring further.

(B) ***Weighted constraints conditioned on time-evolving events (l2r, recsys):*** The deep learning approaches to pattern detection in a static world do not readily support inference over time, or prediction, essential to policy decisions. In a crisis event, as time evolves, new sub-events emerge **[AAAIa 2020]**. We want to learn a function that maps the world's state (Number of people in a Shopping Mall) to a policy (High traffic, a candidate for lockdown). The goal is to train a sequence of models that can estimate the rise in infection and help generate a policy: "Lockdown the place where this event is happening." I develop a semi-deep infusion-based framework that extends an epidemiological model and sequence it with a novel Knowledge-infused Policy Gradient (KiPG) module, which seamlessly integrates bayesian and conditional gradients **[AAAIb 2021]**. Real-world knowledge (e.g. social media chatter, news articles) is infused as weighted constraints conditioned upon the time-evolving events. Bayesian gradients reflect on events that are here to last, and conditional gradients reflect on immediate events with the potential to increase infection cases. The model could precisely estimate the rise in infection rate 15-25 days before it occurs—for instance, information on gathering events, pre-symptomatic patients, or asymptomatic patients. The model output's amenability to an analysis by the expert makes it attractive for real-world use e.g., the Government of Rajasthan **[KDD 2020]**. The developed KiPG forms a critical part of the Knowledge-infused Reinforcement Learning pipeline which has been extended to a recommendation setting on benchmark datasets [**ECML 2021**]. It has also been applied to mental health virtual assistant recommendations to assist clinicians in practice **[ICSC 2019a] (see Figure 4)**.

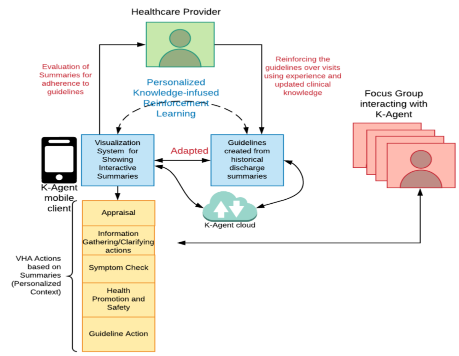

Figure 4: A proposed approach to build virtual assistants for mental health using Knowledge-infused Reinforcement Learning. The assistant will have the capability to generate questions on the fly based on interactive summaries for personalized health suggestions.

(C) ***Matching and Ranking (l2r and recsys):*** I am excited to see tangible real-world impacts resulting from my research at Dataminr Inc. and Jose De Mello Saude Hospital (through the University of Chicago's DSSG Fellowship).
(i) Historical constraints on pattern matching: In the US and Europe, patients' appointments with General Practitioners (GPs) are typically decided based on the doctor's availability. This creates a scenario where patients fail to develop trust with a healthcare professional. So far, understanding the development of trust between patients and their family physicians largely relies on survey-based measures while seldom examining the actual consultation history. I developed a semi-deep K-IL system that models a patient's trust of GPs using the knowledge of consultation history and ICD-10 graphs which describe interaction and change in the severity of condition between interactions. The system can recommend >80% of patients with relevant GPs compared to existing heuristic-based systems in JMS that can do 37% **[DSAA 2018]**. The first ICD-10 knowledge-driven trust-based recommender system went into development at Jose De Mello Saude (JMS) Hospital Network in Portugal. This work was supported by the prestigious **Eric and Wendy Schmidt Data Science for Social Good Fellowship**. The work was featured in **VentureBeat** and described in **Dr. Eric Topol**'s seminal paper in Nature Medicine. *(ii) Abstract knowledge to Rank sub-events and Risks for real-time alerts:* From the influx of millions of tweets during a significant event, humanitarian organizations can't extract emerging risk and high-impact sub-events that are worthy of alerts. Furthermore, the connection between sub-events is challenging to unfold without background information. I built a shallow infusion framework that uses a disaster ontology that I created from Federal Emergency Management Agency archives **[ICSC 2019b]** to cluster potentially connected tweets with mentions of impactful sub-events and risks, as described in the ontology. The system could explain the outcomes through concepts and relationships known to humanitarian organizations **[AAAI 2020]**. Later, it evolved into an integrable module within the alerting application framework and extended with multimodality and the above-described summarization capabilities. The research was awarded **AI for Social Good Fellowship** for its noticeable outcome and publication.

(D) ***Digital Security and Internet Policy (recsys):*** Ethical researchers who want to quote online sources without those sources being googled have little guidance as to how to disguise their phrases. Lubrasky's article on "Re-Identification of *Anonymized* Data" shows that the practice of rewording phrases is often haphazard and ineffective. The KiML algorithm on medical entity normalization **[WWW 2019, Pone 2021]** sees surprisingly new opportunities to study online culture in user identification and user tagging while sharing information. In collaboration with **Prof. Joseph Reagle** in communication studies at **Northeastern University** and Beckman Klein center at **Harvard University**, my research investigates good tactics for ethical information disguise to help researchers disguise their prose by substituting novel words (i.e., swapping infrequently occurring words, such as "toxic" with "radioactive") and rearranging elements of sentence structure **[FM 2022*]**. The research showcases significant improvements over extant services by (a) neutralizing gender using rules (symbolic knowledge), (b) selectively performing single-word or multiple-word substitution using ConceptNet, and (c) removing insignificant elements of sentence structure. Further work in this domain, along with cyber social threats (e.g. radicalization **[CSCW 2019]**, misinformation, negative exposure of online media) is a part of my short term goal

(E) ***Curiosity-driven Question Generation for Conversational Information Seeking (convAI, summ):*** Currently with my collaborators from Allen Institute of Artificial Intelligence, and Samsung Research America, I am exploring ways to develop a sense of curiosity in conversational assistants, predominantly for the task of conversational information seeking. **As a short-term goal**, I am progressing towards enhancing the capabilities of virtual mental health assistants, beyond counseling and suggestive care. They refrain from patient diagnostic assistance because of lack of training on safety constrained and specialized clinical process knowledge (***proknow***). In this work, we introduce a new dataset of diagnostic conversations guided by safety constraints and ***proknow*** that healthcare professionals use (***proknow-data***). We then develop a method for natural language generation (NLG) that collects diagnostic information from the patient in an interactive manner (***proknow-algo***). We demonstrate the limitations of using state-of-the-art large-scale language models on this dataset. ***proknow-algo*** models the process knowledge through a heuristic controller that enables safe, valid, and explainable NLG and achieves improvements in these characteristics 82% of the time. Through both our proposed dataset ***proknow-data*** and our heuristic informed language generation pipeline ***proknow-algo***, we hope to draw the interest of the mental NLP community towards socially impactful problems that not only require collecting novel datasets but also innovation in existing NLP methods **[ACL 2022*]**. I believe related research on Virtual Health Assistants, which also introduce **Trustworthy AI, Conversational Assistance, and Interactive Knowledge-guided Explanations,** would complement and broaden research thrust in data science and AI.

Research Dissemination and Impact

I had the opportunity to publish my research in high-ranked computer science conferences and journals. Prestigious/high impact venues include ACM Hypertext, Web Conference, ECML, CSCW, CIKM, SIGKDD, AAAI, JMIR (IF: 5.43), IEEE Internet Computing (IF: 4.23), PLOS One (IF: 3.24), and PeerJ (IF: 3.09). My research has achieved significant visibility and notoriety through **invited talks** at **BigData Health Science Conference**, **UT Dallas, IIIT Delhi, Harvard CRCS, PyData, Semantic Web Conference, and Nonprofits**. The teaching experience cultivated through tutorials at **ACM Hypertext, ACM CoDS-COMAD**, **and AAAI** conferences, alongside the course I co-instructed, helped me achieve prowess in not only extending my research but also seeking new and pressing research directions that would win NSF, NIH, AFRL, or Industry grants. For instance, **NSF EAGER Award #2133842 about advancing neuro-symbolic AI with deep knowledge infusion** reflects the gravity of my research directions *(lead contributor to the grant)*. Also, I am thrilled to be a *lead contributor* in an **EPSRC-UKRI grant on Time-sensitive sensing of language and user-generated content,** which was awarded in collaboration with **Alan Turing Institute**[5] based on my research on developing methods for understanding changes the causes of change in human behaviour over time in mental health. Further, my research has also attracted the attention of the public through workshops at **ACM SIGKDD, AAAI ICWSM, and Knowledge Graph** conferences. I have been interviewed by Ontotext, TheRegister, and my papers have been covered by global media outlets, including **Computing Research Organization (CRA), Healthline, The Conversation, and Venturebeat**.

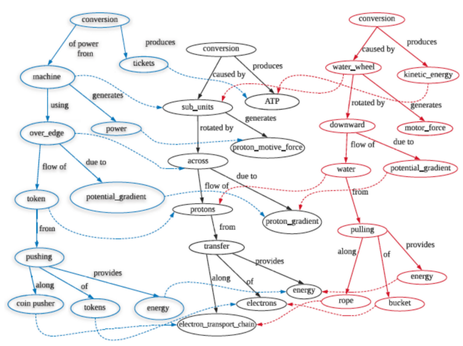

Figure 5: (Left in blue) Potential structure mapping between the coin pushing arcade game (target domain) and oxidative phosphorylation to make ATP (source domain) and (Right in red) between the processes of water being drawn from a well to power a water wheel in a grist mail and oxidative phosphorylation to make ATP. The structure mapping representation is similar on both left and right side.

Vision For the Future

My long-term research goal is to build the next generation of end-to-end neuro-symbolic artificial intelligence frameworks that are explainable, interpretable, and reasonable. Particularly, I want to exercise conscious efforts in developing deep knowledge infusion methods, making technical contributions in ***convAI, recsys, l2r,*** and ***summ*** that support applications in **healthcare, education, cyber social threats, digital security and internet policy, and bioinformatics**. Below, I discuss my future research directions in Core AI and interdisciplinary research that have funding potential.

(i) Core AI Research: So far, I have motivated the applicability of shallow and semi-deep knowledge infusion to provide explainable outcomes in scenarios with no labeled data and it is infeasible to create high-quality testbeds (A). Further, it is computationally hard for a statistical learning approach to make explainable inference in temporal problems with uncertainty (B). In my vision, what is more profound is the attainment of flexibility, consistency, and robustness in KiML algorithms to perform well in cross-domain applications. For instance, a KiML algorithm capable of discerning the

[5] Spending few months as visiting researcher

stratified knowledge in musical chairs processes can help in understanding Enzyme Kinetics, a process in biochemistry. This is called "Learning by Analogy", an instance of Deep KiML that can help any DL model in providing a prediction and explanation without the necessity of labels **[TUT 2020]** (**see Figure 5;** an illustration of analogy between coin pushing arcade game and oxidative phosphorylation). I see its immense potential in education technology, crisis management, and various medical disciplines. Moreover, this vision is of immediate relevance to NSF IIS and NSF CISE focusing on human-center explainable AI. As a prospective faculty in informatics, I seek to explore and devise innovative methods in analogy-based learning and education technology that interface KG and human-centered computing for a variety of application domains.

(ii) Interdisciplinary Research: Interdisciplinary research experiences have broadened my research perspectives and motivated many innovative ideas. For instance, In collaboration with Embibe, an *education* technology enterprise, I am inspecting neural and non-neural KiML algorithms that support mathematical reasoning while solving **math word problems (MWP)** straight from the English narratives. Here the role ***proknow*** is eminent. However, this would require collaboration with faculties in linguistics and education, which I would seek in the university I will be joining. I am also interested in studying **time-evolving user networks** in **spontaneous events**, such as pandemics, crises, etc. In particular, I am curious about the mathematical modeling of short-lived **communities of support seekers and support providers** that are formed on social media using KiML algorithms for dynamic **peer-support group formation**. I believe this research in computational social science would find relevance with faculty researchers in digital humanities. Through tutorials in computational data science conferences, I found overwhelming responses in these research directions **[TUT 2021a, TUT 2021b, TUT 2020]**. With faculties in bioinformatics and biostatistics, I would be interested in exploring the utility of **KG, Causal AI, and Statistics** to study large-scale high-dimensional data on **Early Colorectal Cancer (Bioinformatics).** In particular, seek ways to generate causal explanations with knowledge by extracting causal attributions from BlackBox AI models and corroborating it with information in scientific literature.

(iii) Research Funding: I have had the good fortune to closely work on several proposals with my academic advisors. Some of the pending or soon to be submitted grants led by my advisor to which I have significantly contributed include: **(a)"Analogy-based learning in Biochemistry,"** Agency: NSF Medium, Collaborator: University of Tennessee; Proposed research examines compositional student-generated analogies for a novel AI-assisted interactive learning and assessment with a user logged feedback **(pending)**. **(b) "Virtual Health Assistant (VHA),"** Agency: NSF SCH Medium, Collaborator: UofSC School of Medicine: Proposed research implements the principles of self-monitoring, self-appraisal, and self-management in VHA for personalized and reflective support to patients with moderate mental health conditions. The proposal also lays emphasis on individual and societal implications of information systems and ethical usage of digital assistants **(pending).** Likewise, **(c) "MAESTRO: Psychiatric Process-Guided, Safety Constrained, and Explainable Language Generation in VMHA to Screen and Triage Depression, Anxiety, and PTSD"**, Agency: SONY AI Research, Collaborator: Alan Turing Institute UK **(pending)** is a proposal for developing virtual mental health assistants. In the context of (b) and (c), I intend to explore and extend the problem design in these proposals with the faculties in the University I will join. **(d) "Infant Autism Detection System: Development of an Instrumented, Intelligent Infant Interaction Laboratory for the Prediction of Autism Spectrum Disorder"**, Agency: UofSC Internal seed with planned R01, Collaborator: UofSC Center of Excellence on Autism and Neurodevelopmental Disorders **(Funded).** These experiences enable me to think big, find novel and important fundamental or practical research problems, and convert my creative thinking into clear and convincing grant proposals. With the future research interests given above, I plan to write proposals to get funding support from NSF CRII, NSF CAREER, NSF Core IIS Programs, NIH K21, DoD (ONR, AFRL, AFOSR, etc.), DoE, and others to support my research and to support and train the next generation researchers. I have also been fortunate to have collaborated with a number of stellar researchers both in academia and industry, many of whom have been my mentors in research. The research agenda is very often shaped in wonderful ways through such collaborations, as well as through mentoring and advising graduate students (**see Figure 6**). To that end, I intend to keep nurturing and strengthening my ongoing collaborations and pursue collaboration with scholars within and outside my field.

Vision	Collaboration and Research Grant Funding	Outreach: Education and Training
Methods: • Personalized Knowledge Graph Construction • Deep Knowledge Infusion • Neuro-Symbolic AI • Safe, Explainable, Interpretable, and Tractable AI Systems • Reinforcement Learning **Applications:** • Healthcare • Education Technology • Finance • Online Culture, Social Harms and Crisis Response	**Funding Agencies of Interest:** • NIH (NIMH, NIDA)(e.g. R21, R03) • NSF (e.g. IIS, SCH, CISE) • DoD, DoJ, ONR • Facebook, Google, Samsung Research, Bloomberg, Microsoft **Current Collaborations:** • Weill Cornell Medicine • Alan Turing Institute, UK • University of Kentucky • Northeastern • Harvard CRCS • Wright State and more.	• Recruitment of undergraduates, graduates, and Ph.D. students (with Diversity and Inclusion) • Coordination with Center for Teaching Excellence • Workshops/Tutorials in ACM, IEEE, AAAI, AMIA, and NIH/NSF-sponsored meetings • Invited Keynotes, Talks, and Teaching seminar-level courses

Figure 6: Vision for implementing and executing research in CS and Interdisciplinary fields.