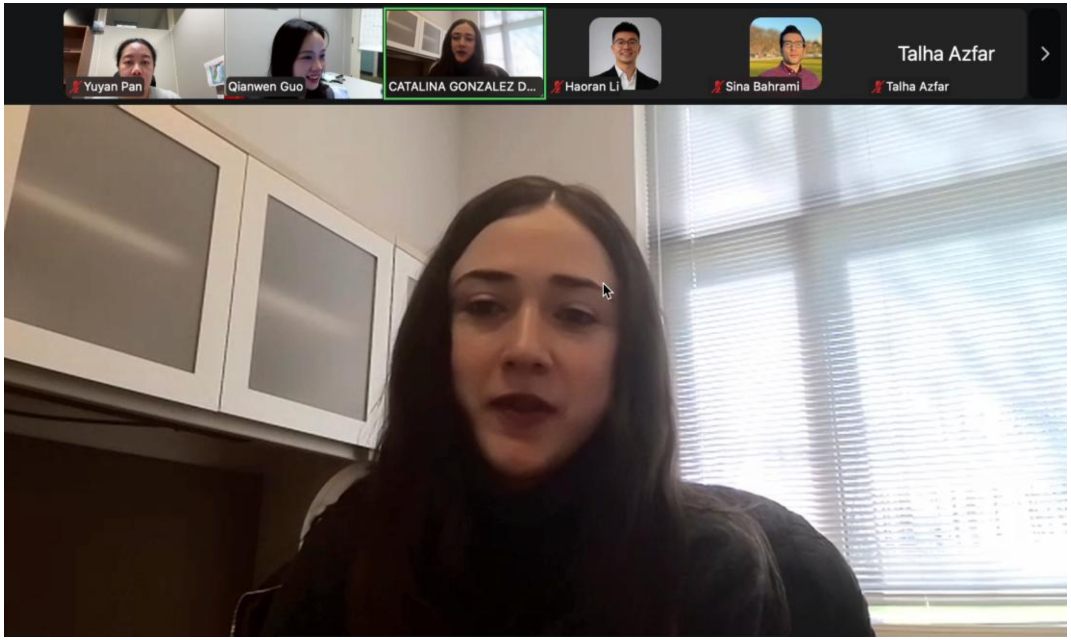
Summary

1. Speaker Information:

- **Name**: Dr. Catalina González-Dueñas, Assistant Professor, George Mason University
- **Research Area**: Uncertainty quantification and long-term resilience under evolving hazard conditions

2. Participant Statistics:

- Total participants: 22 (Academia: 19; Industry/Others: 3).



Summary

3. The Seminar Covered Three Main Research Topics:

(1) Cross-System Risk Modeling under Extreme Events

- Modeling cascading effects across built, natural, and social systems
- Understanding interdependencies and feedback mechanisms in disasters
- Supporting infrastructure planning and resilience assessment

(2) AI + Physics-Integrated Modeling Frameworks

- Graph Neural Networks (GNN) trained on CFD simulations for vegetation-based protection
- Spatiotemporal prediction of hurricane-driven flows in coastal regions
- Physics-informed modeling of debris-driven cascading failures

(3) Efficient Risk Analysis and Decision Support

- Graph-based surrogate models for efficient regional-scale analysis
- Large-scale time-history and probabilistic risk modeling
- Integration of Generative AI (GenAI) for post-disaster damage assessment

Summary

4. Key Questions Discussions:

(1) Decision-making evolution in high-stakes engineering under the integration of AI and traditional models: trust, uncertainty, and model limitations

The primary barrier to adopting AI in high-stakes engineering decision-making, such as building resilience, is trust, as practitioners and stakeholders often remain skeptical of AI-driven outputs. A key limitation is that AI models typically produce deterministic results, whereas real-world decision contexts are inherently uncertain. Therefore, a critical research direction is uncertainty quantification, enabling AI to provide risk ranges and confidence levels rather than definitive answers, thus supporting rather than replacing human decision-making. At the same time, traditional physics-based and numerical models remain essential, as not all problems are suitable for AI, making it important to understand the applicability and limitations of different modeling approaches. Ultimately, AI's role lies in enhancing information processing and situational awareness, but its safe and effective use depends on improving interpretability, reliability, and a deeper understanding of model failures.

Summary

(2) How can we quantify the contribution of physics-based components to the performance of AI models in physics-guided frameworks?

This remains a challenging and largely open research problem. Since AI models are fundamentally data-driven while physics-based models rely on first principles, it is difficult to disentangle how much of the model's performance improvement comes from embedded physical knowledge versus learned data patterns. Existing approaches, such as physics-informed neural networks (PINNs) and graph neural networks (GNNs), incorporate physics either explicitly through equations or implicitly via inductive bias, but they do not provide a direct way to quantify contribution. In practice, the influence of physics is reflected in model design, variable selection, and comparative experiments, and its effectiveness depends on the specific objective, such as improving accuracy, efficiency, or interpretability.

Summary

(3) Can your physics-guided AI models capture interactions between multiple hazards, such as cascading or compound disasters?

Yes, physics-guided AI models can capture interactions among multiple hazards, including cascading and compound events. The key lies in how the problem is abstracted and how the interactions between different hazards are represented within the model. Once these relationships are properly defined, the framework can incorporate them to model complex, multi-hazard scenarios. This approach can also be extended to capture interactions across different types of infrastructure systems, making it a powerful tool for studying resilience in complex environments.