Graph Foundation Models for Recommendation

A Comprehensive Survey

Based on the work by Wu et al. (2025)

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Presentation Outline

Introduction

Recommender Systems overview

Limitations

Current approach challenges

Graph Foundation Models

New paradigm explained

Taxonomy

Categories of GFM-based RS

Challenges & Future

Open issues and directions

Conclusion

Summary and takeaways

Introduction to Recommender Systems

Essentials

- Key in digital landscape
- Enable personalization

Traditional Methods

- Collaborative filtering
- Content-based filtering

Recent Advances

- Deep learning methods
- GNNs and LLMs dominate

The Challenge in Recommendations

Data Types

Structural and textual information

GNN Limitations

Good for structure, poor for text

LLM Limitations

Good for text, poor for complex relations

Current Approaches Compared

GNN-based RS

- Captures higher-order relations
- Models multi-hop neighbors
- Accurate graph-based recommendations
- Can't handle text well

LLM-based RS

- Strong contextual understanding
- Processes textual descriptions
- Struggles with complex relations

Graph Foundation Models (GFMs)

- Pre-trained on large graph data
- Combine GNN and LLM strengths
- Align user preferences efficiently
- Reduce bias, improve precision
- Emergence and homogenization in pre-training
- Adapt to diverse tasks

Taxonomy of GFM-based Recommenders

1

Graph-Augmented LLM

Inject graph info into LLMs

2

LLM-Augmented Graph

Enhance graphs with LLM capabilities

3

LLM-Graph Harmonization

Combine semantic and structural embeddings

Graph-Augmented LLM

Key Challenge

Designing cross-modal interfaces

Approach 1

Token-Level Infusion

Approach 2

Context-Level Infusion

Token-Level Infusion Methods

Syntax-Integrated Injection

- Embed special tokens in input
- Examples: TMF, LLMGR

Syntax-Decoupled Injection

- Append graph embeddings as prefixes/suffixes
- Examples: XRec, COMPASS

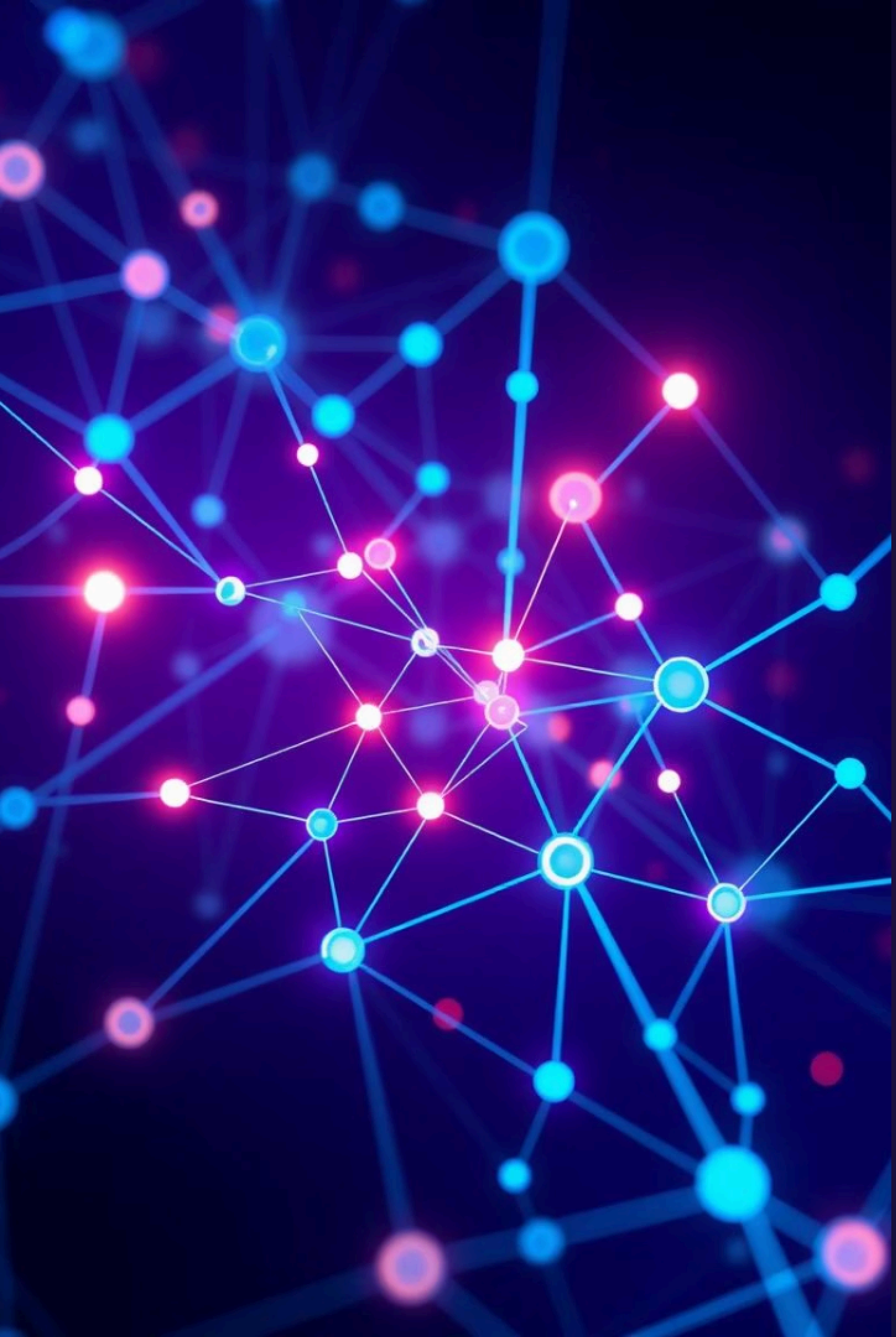
Context-Level Infusion Methods

Explicit Graph-to-Text

- Convert graph to natural language
- Examples: HetGCoT-Rec, KGRec

Implicit Graph Retrieval

- Use GNN embeddings for semantic retrieval
- Examples: CLAKG, URLLM



LLM-Augmented Graph

Core idea: Augment graph data using LLMs

Two main approaches:

1. Topology Augmentation
1. Feature Augmentation

Topology Augmentation

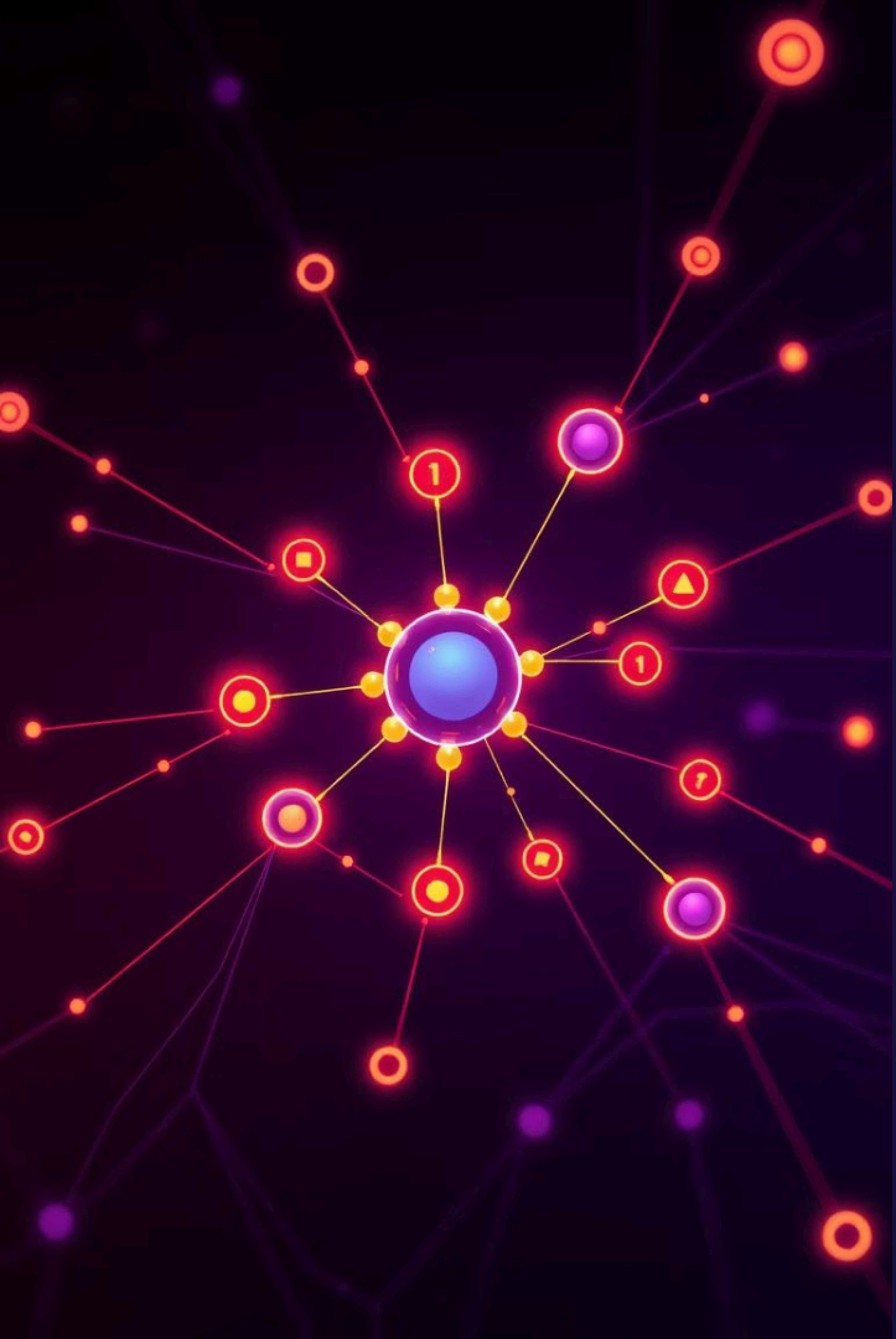
Restructuring graph data with LLMs

Edge-Level Expansion

- Introduces new relationships between nodes
- LLM-KERec assesses item complementarity
- SAGCN extracts user opinions on items

Node-Level Expansion

- Uses auxiliary info as new nodes
- AutoGraph encodes user/item info
- TopicKG generates topic nodes



Feature Augmentation

Enhancing node features without changing topology

Leverages LLM's natural language processing

GaCLLM

LLM performs message passing in GNN

LIKR

LLM analyzes user histories for attributes

P4R

Enhances node textual information

LLM-Graph Harmonization

Balancing textual and structural embeddings

Two main approaches:

- Embedding Fusion
- Embedding Alignment

Embedding Fusion

Unified feature space from both modalities

Embedding Alignment

Maps embeddings into shared space

Embedding Fusion

Combines complementary textual and structural info

DynLLM

Dynamic memory-enhanced fusion

LKPNR

LLMs with knowledge graphs for news recommendation

Embedding Alignment

Reconciling heterogeneous embeddings

Reduces information loss and noise

[DALR]

Contrastive learning alignment

[LLMRec]

Denoised data robustification

[RLMRec]

Contrastive alignment

Challenges

Key challenges for GFM-based recommender systems

Computational Cost & Scalability

High resources, slow inference, memory issues

Robustness Against Noisy Data

Real-world noise, multiple sources, need denoising

More Challenges

Additional challenges for GFM systems

Multi-Modal Fusion

- Diverse data types
- Granularity and semantic gaps
- Integration complexity

Lack of End-to-End Optimization

- Multi-stage complexity
- Resource-intensive
- Need integrated approaches

Knowledge-Preference Gap

- Misalignment between global
- knowledge and preferences

Future Directions

Promising research avenues for GFM

1. Efficient model compression
2. Adaptive graph sparsification
3. Self-supervised denoising
4. Adversarial training
5. Adaptive fusion frameworks
6. End-to-end generative recommendation
7. Preference-aware knowledge adaptation

Conclusion

Key takeaways on GFMs for recommendations

Integration Strengths

GNNs and LLMs enhance recommendations

Main Approaches

Graph-Augmented LLM, LLM-Augmented Graph, Harmonization

Challenges Remain

Several issues to address

Future Potential

Transform personalized recommendations

References

Primary Source

Wu, B., Wang, Y., Zeng, Y., Liu, J., Zhao, J., Yang, C., Li, Y., Xia, L., Yin, D., & Shi, C.

Graph Foundation Models for Recommendation: A Comprehensive Survey. arXiv:2502.08346v2.

Further Reading

Refer to this study for in-depth analysis on GFM methods in recommendation.

Research Impact

Foundational insights shaping future directions in personalized recommendations.

Questions & Answers

Any questions?

We welcome your queries and feedback on Graph Foundation Models for recommendations.

Thank You

Thank you for your attention and engagement throughout this presentation.