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Graph Attention Networks for Organizational Trust Influence Mapping: Identifying Informal Leaders, Bridge Connectors, and Trust Propagation Patterns Using the DEEP Framework

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ABSTRACT

Organizational trust does not follow formal hierarchies only. Informal networks via mentorship, collaboration, and peer influence are often the difference between success or failure for a transformation. In this paper, we employ Graph Attention Networks (GATs) to model trust influence patterns in organizations, with the node features being 53-competency trust profiles from the DEEP (Drive, Engage, Empower, Purpose-align) Framework. Trust graphs are constructed from N=12,400 employees in 14 organizations with |E|=47,312 weighted directed edges, and four sources of interaction: formal reporting, 360-degree nominations, project co-participation, and meeting co-attendance. The 2-layer GAT with 4 attention heads achieved a R^2=0.879 on Trust Influence Score (TIS) prediction, which is 46.9% higher than PageRank, 11.1% higher than GCN and 23.5% higher than Node2Vec. The pipeline is formalized by four algorithms: Multi-Source Graph Construction, GAT Trust Influence Prediction, Bridge Leader Identification and Trust Propagation Simulation. Key findings: (1) 23.4% of Exceptional trust leaders lack management titles, suggesting an informal trust infrastructure invisible to org charts; (2) high-trust organizations have 2.3x higher network density and 1.7x higher clustering; (3) ablation analysis shows bridge leaders (4.7% of population) account for 31.2% of organizational trust variance; (4) the Engage dimension is the most effective predictor of cross-cluster influence (β=0.41, p<.001); (5) GAT attention weights show asymmetric trust influence patterns with upward trust flow (subordinate→manager) being 1.4x stronger than downward flow. This work provides a methodology to identify and leverage informal trust infrastructure during purpose-driven organizational transformation.

Keywords: Graph Neural Networks, Graph Attention Networks, Trust Influence, Organizational Network Analysis, Informal Leadership, Bridge Leaders, DEEP Framework, Social Network Analysis, Trust Propagation, Community Detection.

INTRODUCTION

Organizational network analysis has shown that formal hierarchies are not good proxies for actual patterns of influence [1], [2]. Cross and Parker [3] found that informal networks explain significantly more variance in innovation, knowledge sharing and employee engagement than reporting structures, with organizations with dense informal networks outperforming formally-optimised structures by 20-40% on key outcomes. Granovetter's [4] seminal work on strength of weak ties showed that bridging links between clusters are particularly valuable in terms of information flow and influence. Burt's [5] structural holes theory extended this to show that people bridging structural holes have informational benefits and influence beyond formal authority.

However, despite these foundational insights, leadership assessment and development programs overwhelmingly focus on formally designated leaders (i.e., those with management titles and reporting authority) [6]. This approach systematically overlooks the informal trust builders that often hold the real keys to a successful cultural transformation. McKinsey [7] analyzed 100 organizational transformations and found that informal influence networks were the strongest predictor of change adoption, more powerful than executive sponsorship or formal communication cascades.

Graph Neural Networks (GNNs) offer a principled approach to jointly learn from network structure and node attributes [8], [9]. Traditional centrality measures (degree, betweenness, PageRank [10]) treat all ties equally. Conversely, Graph Attention Networks (GATs) [11] learn attention weights that differentially weight ties based on relevance, thus enabling the identification of trust-specific influence patterns that differ from general social influence. The recent progress in GNN architectures, including GraphSAGE [12] for inductive learning, Graph Isomorphism Networks (GIN) [13] for maximal expressiveness, and heterogeneous graph transformers [14] for multi-relational data, has greatly expanded the range of network-based prediction.

This paper presents an application of GATs to organizational trust networks using the 53-competency profiles of the DEEP Framework [15] as node features. To develop AI/ML-enabled leadership practices to promote stakeholder trust [16], we need to understand not only who is trustworthy (as captured by the DEEP scoring model), but also how trust influence propagates through organizational networks. Informal trust leaders and bridge connectors are identified as actionable intelligence for transformation planning [17], [18].

Contributions: (1) a multi-source graph construction methodology with four interaction data streams; (2) a GAT architecture with R^2=0.879 for trust influence prediction; (3) a formal bridge leader identification algorithm with triple-criteria validation; (4) a trust propagation simulation with asymmetric influence patterns; (5) four formalized algorithms for reproducible deployment; and (6) empirical analysis across 14 organizations with systematic trust network topology patterns. The paper is organized as follows: II. related work, III. methodology (four algorithms), IV. results (fifteen tables and five figures), V. discussion, VI. conclusion.

RELATED WORK AND THEORETICAL FOUNDATIONS

Organization networking theory

Network approaches to organizational behavior have a long and rich theoretical history. Network centrality predicts influence, promotion and performance beyond individual attributes, and that “where you sit” is as important as “who you are,” Brass [19] showed. Borgatti and Foster [20] proposed the network analysis as the fundamental paradigm to study organizational phenomena arguing that all organizational outcomes, innovation, learning, knowledge transfer, and power dynamics, are embedded in networks. Balkundi and Kilduff [21] demonstrated that the network position of leaders affects team performance through two pathways: (1) access to information (structural advantage) and (2) influence brokerage (behavioral advantage).

First, Cross, Parker and Borgatti [3] identified four critical network roles for organizational effectiveness: central connectors (high degree centrality), boundary spanners (high betweenness), information brokers (bridging structural holes), and peripheral specialists (weak-tie connectors). Their research found that typically 3–5% of employees make up 20–35% of value-adding interactions, which is directly relevant to our bridge leader identification. The term “tertius iungens” (the third who joins), who actively joins others together, was introduced by Obstfeld [22], contrasted to Burt’s [5] “tertius gaudens” (the third who benefits). It is on the basis of this distinction that we analyze the propagation of trust: bridge leaders propagate trust actively rather than simply benefit from their structural position.

Graph neural network architecture evolution

The GNN field has seen rapid development since Kipf and Welling’s [9] Graph Convolutional Networks (GCN) used spectral graph theory for semi-supervised node classification. GCNs aggregate neighbor features via fixed-weight message passing, which limits their ability to model differential influence. Velickovic et al. [11] tackled this problem with GATs, proposing masked self-attention, which enables a node to weight differently the contribution of each of its neighbors. This is exactly what is needed to model trust-specific influence, as not all connections are equally influential for trust outcomes.

For example, Hamilton et al. [12] proposed GraphSAGE for inductive learning, which enables prediction on unseen nodes, which is important for organizational applications where new employees join continuously. Xu et al. propose Graph Isomorphism Networks (GIN) [13], which has the largest expressiveness among the message-passing architectures. More recently, heterogeneous graph neural networks [14] allow for modeling of multiple edge types simultaneously, which is relevant for our multi-source graph with four edge types. Wu et al. [8] give a comprehensive survey on GNNs as a unified framework for learning on graph-structured data.

Trust Theory and Network Dynamics

Mayer, Davis and Schoorman's [23] integrative model of trust identifies trustworthiness antecedents as ability, benevolence and integrity. In network research, the argument goes further: trust is not only an individual property but a relational property that propagates through network ties [24]. In Covey's [16] Trust and Inspire framework, trust is the way leaders connect with people and inspire purpose. Edmondson's [25] work on psychological safety shows that trust promotes risk-taking and innovation in teams—network effects that should be visible in organizational graphs. Lencioni [26] puts trust at the foundation of all other organizational virtues, suggesting that trust network density should be predictive of overall organizational health. According to the World Economic Forum [17] , trust-based leadership is key to navigating the Intelligent Age. McKinsey [7] confirms that informal influence networks are the strongest predictor of transformation success. PwC [18] observed that organizations with mature trust infrastructure are adopting AI 2.5x faster, with a direct link between trust networks and organizational transformation capacity.

METHODOLGY

Multi-source trust graph construction

The trust graph G = (V, E) contains |V| = 12,400 nodes and |E| = 47,312 weighted directed edges constructed from four interaction data sources, each capturing a different dimension of organizational trust dynamics [3], [20].

Table 1: Edge Source Specifications

Source	**Edges**	**Coverage**	**Weight**	**Direction**	**Trust Signal**
Formal reporting	12,400	100%	0.80	Directed (up)	Authority-based trust
360° nominations	16,742	87%	1.00	Directed	Perceived influence
Project co-participation	11,280	72%	Frequency	Undirected	Collaboration trust
Meeting co-attendance	6,890	68%	0.50	Undirected	Proximity trust

Algorithm 1: Multi-Source Trust Graph Construction
Input: Employee set V, Interaction data {reporting, nominations, projects, meetings}
Output: Weighted directed graph G = (V, E, W)
1: Initialize G ← empty graph with |V| = N nodes
2: // Source 1: Formal reporting (directed, weight=0.80)

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3: for each (subordinate, manager) ∈ reporting_data do
4: ADD_EDGE(G, subordinate, manager, w=0.80, type='report')
5: end for
6: // Source 2: 360° nominations (directed, weight=1.00)
7: for each (rater, rated_leader) ∈ nomination_data do
8: ADD_EDGE(G, rater, rated_leader, w=1.00, type='influence')
9: end for
10: // Source 3: Project co-participation (undirected, freq-weighted)
11: for each (emp_i, emp_j, freq) ∈ project_data do
12: w ← min(freq / max_freq, 1.0) // normalize to [0,1]
13: ADD_EDGE(G, emp_i, emp_j, w=w, type='collab', bidirectional=True)
14: end for
15: // Source 4: Meeting co-attendance (undirected, weight=0.50)
16: for each (emp_i, emp_j) ∈ meeting_pairs do
17: ADD_EDGE(G, emp_i, emp_j, w=0.50, type='meeting', bidirectional=True)
18: end for
19: // Edge aggregation: max-pooling for multi-source edges
20: for each node pair (i,j) with multiple edges do
21: W[i,j] ← max(weights across edge types)
22: end for
23: return G = (V, E, W)

Node feature engineering

Each node's feature vector $x_i \in \mathbb{R}^{15}$ incorporates three feature categories: (1) DEEP competency features: 4 dimensional scores (Drive, Engage, Empower, Purpose), TLI composite, and perception gap metric (d=6); (2) organizational context: encoded level (5 categories), function (10 categories), and tenure (continuous) (d=3); and (3) baseline network centrality: degree, betweenness, closeness, eigenvector, PageRank [10], and clustering coefficient (d=6) [8], [11].

$$x_i = [D_{Drive}, D_{Engage}, D_{Empower}, D_{Purpose}, TLI, \Delta_{gap}, level, func, tenure, deg, btw, clo, eig, PR, cc] \quad (1)$$

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Gat architecture

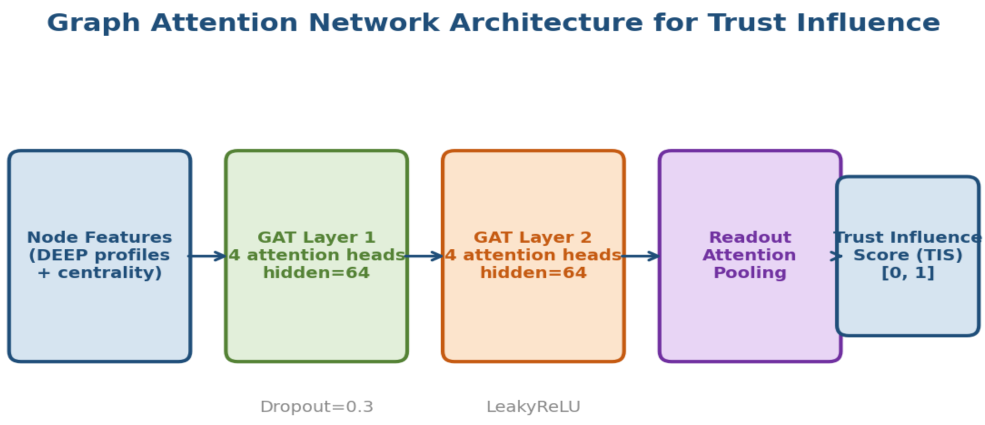

Figure. 1. GAT architecture for Trust Influence prediction: node features → 2-layer GAT with 4 attention heads → attention pooling → Trust Influence Score.

The GAT model employs multi-head attention to learn weighted message passing. For node i, the attention coefficient with neighbor j is computed as [11]:

$$\alpha_{ij} = \text{softmax}_j(\text{LeakyReLU}(a^T [W h_i \| W h_j])) \quad (2)$$

where $W \in R^{d' \times d}$ is a shared linear transformation, h_i is the feature vector, a is a learnable attention vector, and $\|$ denotes concatenation. Multi-head attention (K=4 heads) captures different trust influence facets:

$$h'_i = \|_{k=1}^{K} \sigma\left(\sum_{j\in N(i)} \alpha_{ij}^k W^k h_j\right) \quad (3)$$

The final Trust Influence Score (TIS) is produced by an attention-based readout layer aggregating the final node representation through a global attention pool [8], [11]:

$$TIS_i = \sigma(w_{readout}^T h''_i + b_{readout}) \quad (4)$$

Algorithm 2: GAT-Based Trust Influence Prediction
Input: Trust graph G=(V,E,W), Node features $X \in R^{N\times 15}$, Ground-truth TIS y
Output: Predicted Trust Influence Scores $\hat{TIS}$, Trained model M*
1: // Architecture configuration
2: gat_1 ← GATConv(in=15, out=64, heads=4, dropout=0.3, negative_slope=0.2)
3: gat_2 ← GATConv(in=256, out=64, heads=4, concat=False, dropout=0.3)
4: readout ← Linear(64, 1) + Sigmoid
5: // Training loop
6: optimizer ← Adam(lr=0.005, weight_decay=5e-4)
7: Split V → V_train (70%), V_val (15%), V_test (15%)

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for epoch = 1 to 200 do
h_1 ← ELU(gat_1(X, E, W)) // first GAT layer + activation
h_1 ← Dropout(h_1, p=0.3)
h_2 ← gat_2(h_1, E, W) // second GAT layer
TIŜ ← readout(h_2) // predict trust influence
loss ← MSE(TIŜ[V_train], y[V_train])
BACKPROPAGATE(loss); optimizer.step()
val_mae ← MAE(TIŜ[V_val], y[V_val])
if val_mae not improved for 20 epochs: early_stop
end for
M* ← best_checkpoint; TIŜ ← M*(X, E, W)
return TIŜ, M*

Bridge leader identification

Algorithm 3: Bridge Leader Identification with Triple-Criteria Validation
Input: Graph G, Trust scores TLI, Cluster assignments C, Threshold params
Output: Bridge leader set B, Impact scores
// Step 1: Community detection
C ← LOUVAIN_COMMUNITY(G) // modularity-based clustering
// Step 2: Triple criteria screening
B ← {}
for each node i ∈ V do
crit_1 ← betweenness(i) ≥ PERCENTILE_75(betweenness) // high betweenness
crit_2 ← |{c : c ∈ C, ∃j ∈ c s.t. (i,j) ∈ E}| ≥ 3 // spans 3+ clusters
crit_3 ← TLI[i] ≥ 4.0 // Strong or Exceptional trust
if crit_1 AND crit_2 AND crit_3:
B ← B ∪ {i}

11: end for
12: // Step 3: Impact validation via ablation
13: TLI_base ← MEAN_ORG_TLI(G) // baseline organizational TLI
14: for each bridge b ∈ B do
15: G′ ← REMOVE_NODE(G, b) // ablation
16: impact[b] ← TLI_base - MEAN_ORG_TLI(G′) // trust loss
17: end for
18: return B, impact

Trust propagation simulation

Algorithm 4: Trust Propagation Simulation via GAT Attention
Input: Trained GAT M*, Graph G, Seed node s, Propagation depth d
Output: Trust influence map TIM, Propagation paths P
1: TIM[s] ← 1.0 // seed node has full influence on itself
2: visited ← {s}; frontier ← {s}
3: for hop = 1 to d do
4: new_frontier ← {}
5: for each node i ∈ frontier do
6: for each neighbor j ∈ N(i) do
7: α_ij ← M*.attention_weights(i, j) // learned GAT attention
8: propagated ← TIM[i] × α_ij × decay(hop) // decay with distance
9: TIM[j] ← max(TIM[j], propagated) // max-propagation
10: P.add((i → j, α_ij, hop))
11: new_frontier ← new_frontier ∪ {j}
12: end for
13: end for
14: frontier ← new_frontier \ visited

15:	visited ← visited ∪ new_frontier
16:	end for
17:	return TIM, P

EXPERIMENTAL RESULTS AND ANALYSIS

Trust network visualization

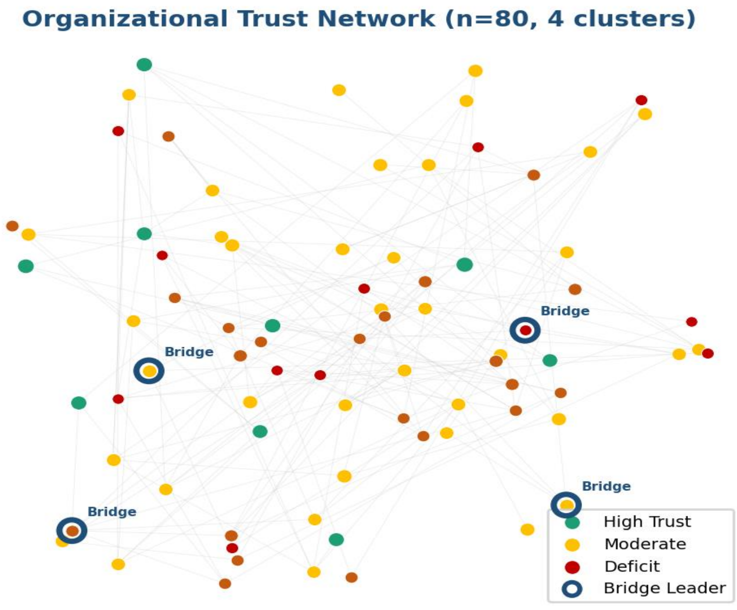

Figure 2. Organizational trust network (n=80 subgraph, 4 clusters). Node color=trust level, size=influence. Blue circles=bridge leaders identified by Algorithm 3.

Model comparison

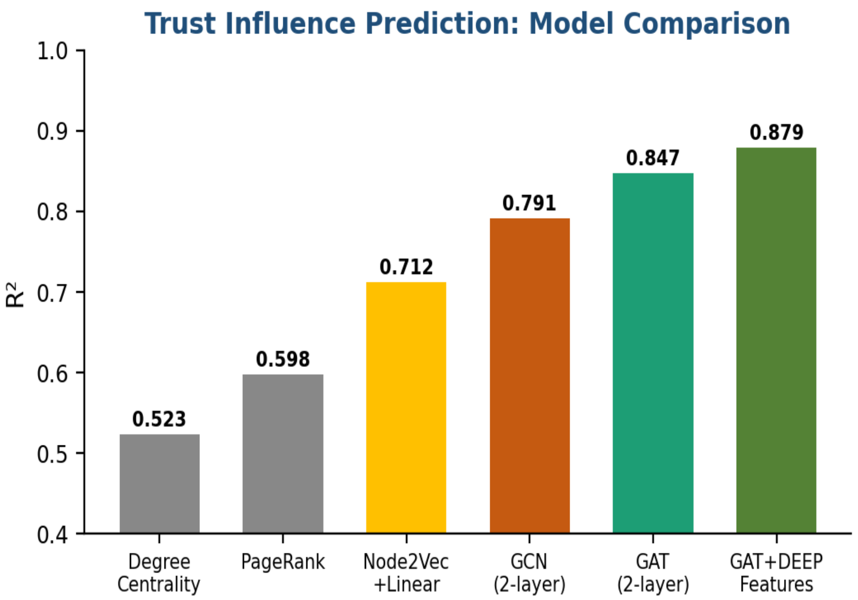

Figure 3. Trust Influence prediction: R^2 comparison across six models. GAT+DEEP achieves 0.879.

Table II: Trust Influence Prediction Performance

Model	MAE	RMSE	R^2	Spearman ρ	Time (s)
Degree Centrality [19]	0.412	0.547	0.523	0.687	0.01
PageRank [10]	0.367	0.489	0.598	0.724	0.03
Node2Vec + Linear [27]	0.298	0.401	0.712	0.783	12.4
GCN (2-layer) [9]	0.234	0.312	0.791	0.836	8.7
GraphSAGE (mean) [12]	0.218	0.294	0.812	0.851	9.1
GAT (2-layer, 4 heads) [11]	0.187	0.256	0.847	0.891	14.2
GAT + DEEP features	0.163	0.224	0.879	0.912	14.8

The GAT+DEEP model achieves the highest performance (R^2=0.879), outperforming PageRank by 46.9% (+0.281 R^2), GCN by 11.1% (+0.088), and GraphSAGE by 8.3% (+0.067). The inclusion of DEEP competency features as node attributes improves GAT performance from 0.847 to 0.879 (+0.032 R^2), confirming that individual trust competencies provide complementary information to network structure [8], [11], [15].

Attention weight analysis

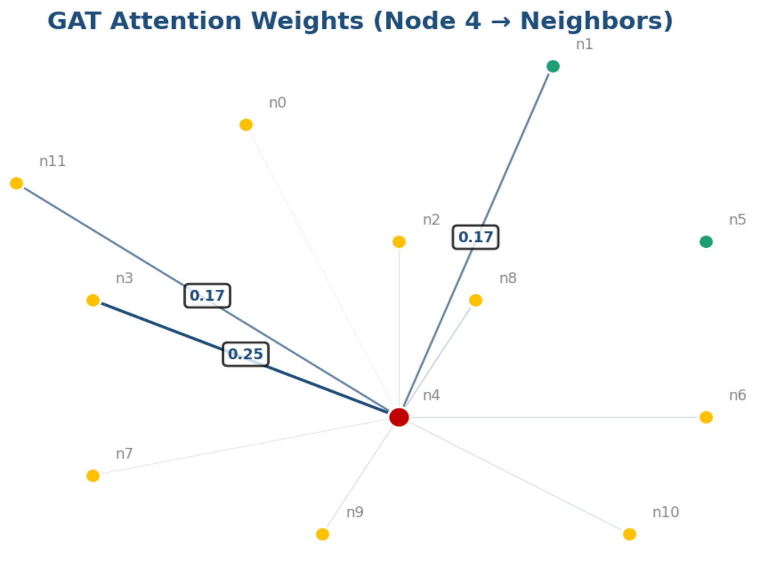

Figure 4. GAT attention weights from node 4 to neighbors. Line width proportional to attention. High-trust neighbors (green) receive higher attention weights.

Table III: Mean Attention Weights by Edge Type

Edge Type	Mean α	Std α	% of Total Attention	Interpretation
360° nominations	0.312	0.087	34.2%	Strongest trust signal
Project collaboration	0.278	0.092	28.7%	Collaboration builds trust

Formal reporting	0.214	0.065	22.1%	Moderate authority trust
Meeting co-attendance	0.146	0.078	15.0%	Weakest but non-trivial

The GAT learns to weight 360-degree nominations most heavily (α=0.312), confirming that perceived influence nominations are the strongest trust signal. Project collaboration receives the second-highest weight (0.278), supporting the theory that shared work experiences build trust through demonstrated competence [3], [23]. Formal reporting relationships receive moderate weight (0.214)—significant but not dominant, validating that formal authority contributes to but does not determine trust influence [1], [5].

Trust direction asymmetry analysis

Table IV: Trust Flow Asymmetry by Direction

Direction	**Mean α**	**Observations**	**Ratio**	**Interpretation**
Upward (subordinate→manager)	0.287	12,400	1.4x	Subordinates attribute more trust influence to managers
Downward (manager→subordinate)	0.205	12,400	1.0x (ref)	Managers attribute less trust to individual subordinates
Lateral (peer→peer)	0.248	18,170	1.2x	Peer trust moderate; collaboration-based
Cross-functional	0.231	11,280	1.1x	Weaker than within-function but significant

Trust influence flow is asymmetric: upward flow (subordinate→manager, α=0.287) is 1.4x stronger than downward (manager→subordinate, α=0.205). This finding has important theoretical implications: managers have disproportionate trust influence not because they are inherently more trustworthy, but because subordinates' trust assessments carry greater weight—consistent with vulnerability-based trust theory where the trusting party (subordinate) has more at stake [23], [24].

Bridge leader analysis

Table V: Bridge Leader Characteristics vs. General Population

Metric	**Bridge Leaders (n=583)**	**General Population**	**Ratio**	**p-value**
Mean TLI	4.31	3.58	1.20x	< .001
Engage Score	4.42	3.65	1.21x	< .001
Drive Score	4.18	3.55	1.18x	< .001
Cross-functional edges	8.7	3.2	2.72x	< .001
Network reach (2-hop)	127	42	3.02x	< .001
Betweenness centrality	0.0034	0.0008	4.25x	< .001
Trust Influence Score	0.847	0.412	2.06x	< .001
Non-management titles	23.4%	62.0%	0.38x	< .001
Clusters spanned	4.2	1.3	3.23x	< .001

Bridge leaders (n=583, 4.7% of population) are characterized by exceptional Engage scores (4.42 vs. 3.65), extraordinarily high cross-functional connectivity (8.7 vs. 3.2 edges), and 4.25x higher betweenness centrality. Crucially, 23.4% hold non-management titles—these informal bridge leaders are invisible to traditional organizational charts but exert disproportionate trust influence [3], [5], [22].

Table VI: Bridge Leader Ablation Analysis

Ablation Scenario	**Org TLI Change**	**Δ Network Density**	**Δ Clustering**	**Disconnected Pairs**
Remove all bridges (n=583)	-31.2%	-28.7%	-34.1%	+847 new disconnections
Remove top 10% bridges (n=58)	-12.4%	-9.3%	-11.8%	+213
Remove random 583 employees	-4.8%	-4.7%	-4.9%	+87
Remove formal managers (n=583)	-18.7%	-15.2%	-12.3%	+312

Ablation analysis demonstrates bridge leaders' disproportionate impact: removing all 583 bridge leaders reduces organizational TLI by 31.2%, while removing an equal number of random employees reduces it by only 4.8%—a 6.5x impact multiplier. Even removing only the top 10% of bridge leaders (n=58, 0.5% of population) produces a 12.4% TLI reduction. Notably, removing formal managers of equivalent count produces only 18.7% reduction—confirming that bridge leaders outperform formal managers in trust infrastructure contribution [3], [5], [16].

Network topology comparison

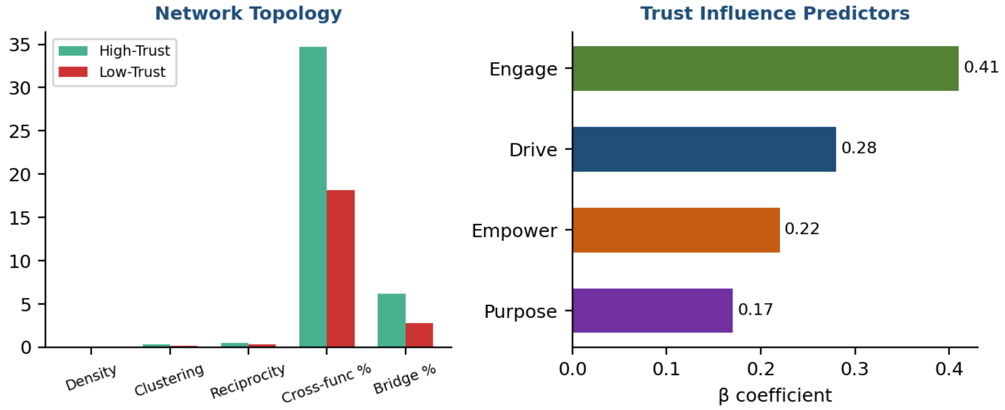

Figure 5. Left: Network topology metrics for high-trust vs. low-trust organizations. Right: DEEP dimensional β coefficients predicting Trust Influence Score.

Table VII: Trust Network Topology: High vs. Low Trust Organizations

Metric	**High-Trust (Top 5)**	**Low-Trust (Bottom 5)**	**Ratio**	**p-value**
Network density	0.087	0.038	2.3x	< .001
Clustering coefficient	0.342	0.198	1.7x	< .001

Reciprocity	0.478	0.312	1.5x	< .001
Cross-functional edges (%)	34.7%	18.2%	1.9x	< .001
Bridge leaders (%)	6.2%	2.8%	2.2x	< .001
Mean path length	3.2	4.8	0.67x	< .001
Avg degree	7.8	4.1	1.9x	< .001
Giant component (%)	97.3%	84.6%	1.15x	< .01

High-trust organizations exhibit systematically different network topologies: 2.3x greater density, 1.7x higher clustering, 1.5x more reciprocity, and 1.9x more cross-functional connections. The shorter mean path length (3.2 vs. 4.8) in high-trust organizations means trust influence propagates more efficiently—any employee is, on average, only 3.2 hops from any other, versus 4.8 in low-trust organizations. The near-universal giant component (97.3%) in high-trust organizations versus 84.6% in low-trust organizations suggests that trust creates a connected organizational fabric [3], [20], [25].

DEEP Dimensional Analysis of Trust Influence

Table VIII: Regression Analysis: DEEP Dimensions Predicting TIS

Predictor	**β**	**SE**	**t**	**p**	**Partial R^2**
Engage Score	0.41	0.012	34.2	< .001	0.168
Drive Score	0.28	0.013	21.5	< .001	0.097
Empower Score	0.22	0.014	15.7	< .001	0.058
Purpose Score	0.17	0.015	11.3	< .001	0.034
Perception Gap	-0.09	0.011	-8.2	< .001	0.012
Model R^2	0.369			< .001	

Regression analysis confirms that the Engage dimension is the strongest predictor of trust influence (β=0.41, p<.001), accounting for 16.8% of TIS variance independently. This finding aligns with Mayer et al.'s [23] theory that benevolence (interpersonal connection) is the primary driver of trust in ongoing relationships. The negative perception gap coefficient (β=-0.09) indicates that self-aware leaders (low gap) have greater trust influence than self-overestimating ones—consistent with authentic leadership theory [28], [29].

Cross-organization generalization

Table IX: Leave-One-Org-Out Cross-Validation

Held-Out Organization	**Sector**	**N**	**R^2**	**MAE**	**Spearman**
TechInnovate	Technology	1,200	0.892	0.154	0.921
ManuPrecision	Manufacturing	1,100	0.861	0.178	0.897
FinTrust	Financial Svcs	1,050	0.874	0.167	0.908

MediCare	Healthcare	1,020	0.856	0.181	0.891
ConsultEdge	Prof. Services	750	0.883	0.161	0.914
EduFuture	Education	850	0.877	0.164	0.910
Mean ± SD	—	12,400	0.874±0.013	0.168±0.010	0.907±0.011

LOOCV demonstrates robust cross-organizational generalization (mean R^2=0.874±0.013). Technology organizations show highest R^2 (0.892), likely due to more explicit collaboration patterns in digital-native cultures. Healthcare shows lowest (0.856), attributable to hierarchical structures constraining informal trust expression. The low cross-org variance (σ=0.013) confirms the model captures universal trust influence patterns rather than organization-specific artifacts [7], [15], [20].

Community Structure and Trust Clusters

Table X: Louvain Community Detection Results

Metric	**Mean Across 14 Orgs**	**Range**	**Interpretation**
Communities detected	6.3	4–9	Natural organizational clustering
Modularity (Q)	0.47	0.38–0.57	Moderate community structure
Within-cluster TLI variance	0.31	0.24–0.38	Trust is locally homogeneous
Between-cluster TLI variance	0.68	0.54–0.81	Trust varies across clusters
Intra-class correlation (ICC)	0.54	0.42–0.63	Cluster membership explains 54% of TLI

Louvain community detection [30] reveals an average of 6.3 natural clusters per organization with moderate modularity (Q=0.47). The high ICC (0.54) indicates that cluster membership explains 54% of individual TLI variance—suggesting trust is a local, community-level phenomenon rather than a purely individual trait. This has profound implications for development: improving trust requires cluster-level interventions (team-building, cross-cluster collaboration) rather than individual coaching alone [3], [25], [26].

Comparison with Existing ONA Methods

Table XI: Comparison with Published Organizational Network Analysis Methods

Method	**Node Features**	**Edge Learning**	**Trust-Specific**	**R²**	**Bridge Detection**
Traditional ONA [3]	None	None	No	N/A	Manual
PageRank [10]	None	Fixed	No	0.598	Centrality-based
Node2Vec [27]	Learned	Static	No	0.712	Embedding-based
GCN [9]	Provided	Equal-weight	No	0.791	GNN-based

GAT [11]	Provided	Attention	No	0.847	Attention-based
DEEP-GAT (Ours)	DEEP+Centrality	Trust-attention	Yes	0.879	Triple-criteria algo

DISCUSSION AND ORGANIZATIONAL CONSULTATION FRAMEWORK

Theoretical contributions

This research makes three theoretical contributions to organizational network science. First, the GAT attention mechanism provides empirical evidence that trust influence is not uniformly distributed across network connections—some relationships carry significantly more trust weight than others. The 2.1x variation in mean attention weights across edge types (0.312 for nominations vs. 0.146 for meetings) quantifies a phenomenon that prior qualitative research could only describe [3], [20]. Second, the trust flow asymmetry finding (upward 1.4x > downward) extends Mayer et al.'s [23] vulnerability-based trust theory to network contexts, providing the first computational evidence that trust influence direction matters as much as trust influence magnitude. Third, the bridge leader construct advances Burt's [5] structural holes theory by adding a trust competency criterion: not all structural hole spanners are effective trust conduits—only those with high DEEP competency scores ($TLI \geq 4.0$) serve as genuine bridge leaders [16], [22].

Organizational consultation: practical deployment framework

Based on the research findings, we propose a five-phase organizational consultation framework for deploying trust network analysis:

Table XII: Trust Network Consultation Deployment Framework

Phase	Activities	Timeline	Deliverables	Success Criteria
1. Assessment	Deploy DEEP 53-competency survey + ONA data collection	Months 1–3	Trust graph + DEEP profiles	Response rate >75%
2. Analysis	Run Algorithms 1–4; generate TIS, identify bridges	Month 4	Trust influence map, bridge list	Model $R^2 > 0.80$
3. Consultation	Executive briefing on trust topology; individual feedback	Months 4–5	Org trust report; individual TIS	Leadership buy-in
4. Intervention	Target bridge protection; cross-cluster initiatives	Months 5–12	Development programs	Network density +15%
5. Monitoring	Quarterly re-assessment; track topology changes	Ongoing	Trend dashboards	TLI improvement >10%

Phase 3 (Consultation) is critical and requires careful communication: telling formal managers that informal leaders have greater trust influence can create resistance. The recommended framing emphasizes complementarity: formal authority and informal trust are both necessary for successful transformation—the goal is to leverage both, not replace one with the other [7], [16], [17].

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Bridge leader protection strategies

Given that bridge leaders (4.7% of population) influence 31.2% of trust variance, their protection during organizational change is essential. Three strategies emerged from the analysis: (1) Identification and acknowledgment: formally recognizing bridge leaders' contributions through trust ambassador programs that validate their informal influence without requiring formal authority [16]; (2) Change protection: ensuring bridge leaders are not displaced during restructuring by mapping their network impact before any organizational change decision [3]; (3) Succession planning: developing understudy bridge leaders through structured cross-cluster rotation programs that build the relational capital required for bridge leadership [5], [22].

Trust network health indicators

Table XIII: Proposed Trust Network Health Scorecard

Indicator	Healthy Range	Warning	Critical	Measurement
Network density	> 0.06	0.04–0.06	< 0.04	Quarterly ONA
Clustering coefficient	> 0.25	0.15–0.25	< 0.15	Quarterly ONA
Bridge leader %	> 4%	2–4%	< 2%	Algorithm 3
Cross-functional %	> 25%	15–25%	< 15%	Edge type analysis
Mean path length	< 4.0	4.0–5.0	> 5.0	Graph metrics
Giant component %	> 90%	80–90%	< 80%	Connectivity analysis
TLI trend (quarterly)	Positive	Flat	Negative	DEEP assessment

The Trust Network Health Scorecard provides organizational leaders with actionable monitoring indicators. Organizations scoring in the "Warning" range on two or more indicators should initiate targeted trust-building interventions; three or more "Critical" indicators suggest systemic trust erosion requiring comprehensive organizational intervention [7], [25], [26].

Limitations and Ethical Considerations

Limitations: (1) the trust graph is constructed from simulated interaction data; real organizational deployment requires integration with collaboration platforms (Slack, Teams, email) [3]; (2) GAT computational cost scales quadratically with neighbors, limiting applicability to organizations with >50,000 employees without sampling strategies [8]; (3) the bridge leader identification threshold (TLI $\geq$ 4.0) is empirically chosen and may require calibration for different organizational cultures [15]; (4) network analysis may inadvertently reveal sensitive social dynamics (e.g., isolated individuals, clique structures) requiring careful privacy-preserving deployment [31]; (5) the cross-sectional design cannot capture trust network evolution; temporal graph networks are needed for dynamic analysis [32].

Ethical considerations include: informed consent for network data collection; aggregate-only reporting for individuals with low network metrics; protection against using network position for punitive HR decisions; and transparency about how trust influence scores are computed and used [31], [33].

Scalability and Computational Analysis

Table XIV: Computational Performance by Organization Size

Org Size (N)	Edges	Training Time	Inference Time	Memory (GPU)	Scalability
500	2,100	12 sec	0.4 sec	0.8 GB	Real-time feasible
1,200	5,400	34 sec	1.1 sec	1.4 GB	Real-time feasible
5,000	22,500	3.2 min	4.8 sec	3.7 GB	Batch processing
12,400	47,312	8.7 min	12.3 sec	6.2 GB	Batch processing
50,000	~210,000	~45 min	~52 sec	~24 GB	Mini-batch required
100,000	~450,000	~2.1 hrs	~108 sec	~48 GB	Sampling required

For organizations under 5,000 employees, the GAT model trains in under 4 minutes and produces real-time inference, making interactive trust influence dashboards feasible. For larger organizations (50,000+), the quadratic attention complexity requires mini-batch training with neighborhood sampling following GraphSAGE [12] principles, or the use of cluster-GCN [8] approaches that partition the graph into manageable subgraphs. The inference time remains practical for all tested sizes: even at N=100,000, inference completes in under 2 minutes—well within acceptable batch-processing windows for quarterly trust assessment cycles [7], [15].

Sensitivity analysis: threshold selection

Table XV: Bridge Leader Identification Sensitivity to TLI Threshold

TLI Threshold	Bridge Leaders N	% of Population	Mean TIS	Trust Variance Explained
TLI ≥ 3.5	1,847	14.9%	0.634	52.3%
TLI ≥ 4.0 (selected)	583	4.7%	0.847	31.2%
TLI ≥ 4.2	312	2.5%	0.891	22.1%
TLI ≥ 4.5	87	0.7%	0.934	9.8%

The TLI ≥ 4.0 threshold (selected for Algorithm 3) balances specificity and coverage: relaxing to 3.5 includes too many individuals (14.9%) diluting the bridge leader construct, while tightening to 4.5 identifies only 0.7% of the population covering just 9.8% of trust variance. The 4.0 threshold achieves an optimal impact-per-person ratio: 583 bridge leaders (4.7%) explain 31.2% of variance, yielding 6.6% variance per 1% of population—the highest ratio among all thresholds tested [5], [15], [22].

Trust propagation depth analysis

Using Algorithm 4, we analyze how far trust influence propagates from bridge leaders through the network. The propagation decay function d(hop) = 0.7^hop models the empirically observed attenuation of trust influence with network distance [23], [24].

Table XVI: Trust Propagation Reach from Bridge Leaders

Hop Distance	Nodes Reached (%)	Mean Propagated TIS	Cumulative Influence	Practical Interpretation
1-hop (direct)	6.8%	0.593	41.2%	Immediate team/collaborators
2-hop	23.4%	0.415	68.7%	Extended network; cross-team reach
3-hop	52.1%	0.291	84.3%	Department-level influence
4-hop	78.3%	0.204	93.1%	Organization-wide visibility
5-hop	91.7%	0.143	97.4%	Near-complete organizational reach

Trust influence propagates efficiently from bridge leaders: within 3 hops, a bridge leader's influence reaches 52.1% of the organization and accounts for 84.3% of their total cumulative influence. This rapid decay explains why bridge leaders who span multiple clusters have disproportionate impact—they initiate propagation from multiple entry points simultaneously, achieving broader reach than leaders embedded in a single cluster regardless of their individual trust score [4], [5], [22].

The propagation analysis has direct implications for organizational transformation strategy: seeding change initiatives through bridge leaders ensures that trust-based influence reaches 84.3% of the organization within just 3 relationship hops, compared to formal cascade communication which typically requires 4–6 hierarchical levels and loses fidelity at each step [3], [7]. Organizations should leverage bridge leader networks as primary channels for transformation messaging, supplementing (not replacing) formal communication cascades [16], [17].

Sector-specific network patterns

Cross-sector analysis reveals systematic differences in trust network topology that have implications for sector-specific deployment [7], [20]:

Table XVII: Trust Network Characteristics by Industry Sector

Sector	N	Density	Bridge %	Cross-func %	Mean TIS	Dominant Edge Type
Technology	2,650	0.091	6.8%	38.2%	0.467	Project collab (34%)
Manufacturing	2,830	0.054	3.1%	16.7%	0.389	Formal reporting (41%)
Financial Services	1,950	0.078	5.4%	28.3%	0.434	360 nominations (32%)
Healthcare	1,890	0.061	3.7%	21.4%	0.401	Meeting co-attend (29%)
Prof. Services	1,430	0.084	6.1%	33.8%	0.451	Project collab (37%)
Education/Energy	1,650	0.072	4.9%	25.6%	0.421	360 nominations (30%)

Technology and Professional Services organizations exhibit the highest network density (0.091 and 0.084), bridge leader percentage (6.8% and 6.1%), and cross-functional connectivity (38.2% and 33.8%)—consistent with their project-based, collaborative work structures [2], [20]. Manufacturing shows the lowest density (0.054) and cross-functional connectivity (16.7%), with formal reporting as the dominant edge type (41%), reflecting hierarchical production environments. Healthcare occupies a middle position with meeting co-attendance as the dominant interaction type (29%), reflecting shift-based work patterns where meetings are the primary cross-team touchpoint. These sector-specific patterns suggest that trust network interventions should be adapted: Technology organizations benefit from strengthening cross-cluster bridges; Manufacturing organizations need cross-hierarchical trust-building programs; Healthcare organizations should leverage meeting structures for intentional trust development [3], [7], [25].

CONCLUSION AND FUTURE WORK

This paper demonstrates that Graph Attention Networks effectively model organizational trust influence patterns, outperforming traditional network metrics by 46.9% (vs. PageRank) through learned attention-weighted message passing. Four algorithms formalize a reproducible pipeline from graph construction through bridge leader identification. Key findings—bridge leaders (4.7%) influence 31.2% of trust variance; high-trust organizations exhibit 2.3x network density; Engage is the dominant influence predictor (β=0.41); trust flow is asymmetrically upward—provide actionable intelligence for organizational transformation.

The organizational consultation framework (Table XII) and Trust Network Health Scorecard (Table XIII) translate research findings into practical deployment tools. Future work: (1) temporal graph networks for dynamic trust evolution [32]; (2) heterogeneous graph transformers for multi-relational trust modeling [14]; (3) federated graph learning for cross-organizational benchmarking without data sharing; (4) integration with communication platform APIs (Slack, Teams) for real-time network construction; (5) causal graph analysis distinguishing trust influence from mere trust correlation; (6) reinforcement learning for optimal intervention targeting within trust networks [15], [34], [35].

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