# Governance (of the research process)

| Criteria | Performance indicators (action) | | Perception indicators | Key actors |
|---|---|---|---|---|
| | Process indicators | Outcome | | |
| **Openness** | | | | |
| **Participation** | | | | |
| **Accountability** | | | | |
| **Effectiveness** | | | | |
| **Coherence** | | | | |

# Public – multiactor engagement (including the researchers)

| *Criteria* | *Performance indicators (action)* | | *Perception indicators* | *Key actors* |
|---|---|---|---|---|
| | *Process indicators* | *Outcome* | | |
| *Policies,*<br>*Regulation*<br>*Frameworks*<br>*…* | • Collaboration across 3 institutions (Stanford University, Kumo.AI, NVIDIA)<br>• Use of standardized benchmark (RelBench) developed by community<br>• Addressing real-world data challenges in regulated sectors (healthcare, finance) | • Research findings applicable to enterprise data management<br>• Contribution to open-source ML/AI frameworks<br>• Potential influence on future database and AI standards | • Industry recognition (NVIDIA collaboration indicates practical relevance)<br>• Academic validation through conference submission<br>• Community interest (GitHub repository accessibility) | Academic researchers, Industry practitioners (Kumo.AI, NVIDIA), Database administrators, ML engineers, Enterprise data scientists |
| *Event and initiative making*<br>*Attention*<br>*creation* | • Publication of preprint on arXiv (open access)<br>• GitHub repository for code sharing<br>• Documentation through comprehensive appendix and examples | • Public availability of research methodology<br>• Reproducible research through open code<br>• Knowledge transfer to broader ML community | Accessibility of materials to researchers<br>Clarity of documentation for replication<br>Community uptake of methods | Researchers, PhD students, Data scientists, ML practitioners, Open-source contributors |
| *Competence building* | • Detailed methodology documentation<br>• Step-by-step implementation guidelines<br>• Comprehensive appendix with experimental details<br>• Ablation studies explaining component importance | • Enhanced understanding of graph transformers for relational data<br>• Transferable skills in RDL methodology<br>• Best practices for handling temporal, heterogeneous data | • Usefulness of documentation for learning<br>• Clarity of technical explanations<br>• Ability to reproduce and extend the work | PhD students, Early-career researchers, ML engineers, Data scientists |

# Gender equalities

| Criteria | Performance indicators (action) | | Perception indicators | Key actors |
|---|---|---|---|---|
| | Process indicators | Outcome | | |
| **Gender Equalities**<br>**(as criteria to differentiate and correctly include the research participants)** | • Gender-disaggregated analysis potential in datasets (e.g., customer data, user interactions)<br>• Awareness of bias in training data from real-world databases<br>• Fair representation in dataset selection across domains | • Models that don't discriminate based on demographic features<br>• Potential to analyze gender-related patterns in e-commerce, social networks<br>• Consideration of fairness in predictive modeling | • Awareness of potential biases in relational data<br>• Consideration of fairness in model evaluation<br>• Sensitivity to demographic disparities in predictions | Ethics review boards, Dataset curators, ML fairness researchers, Domain experts |
| **Gender equalities**<br>**(as a criterion to balance and characterize the research team)** | • Multi-institutional collaboration (Stanford, Kumo.AI, NVIDIA)<br>• Diverse authorship team with 8 contributors<br>• Equal opportunity for contribution (author list) | • Collaborative research across institutions<br>• Diverse perspectives in problem-solving<br>• Inclusive research environment | • Team members' sense of equal contribution<br>• Collaborative work environment<br>• Recognition of all contributors | Principal investigators (Vijay Prakash Dwivedi, Jure Leskovec), Co-authors, Institutional leadership, Funding agencies |

# From Scientific Education to scientific citizenship

| *Criteria* | *Performance indicators (action)* | | *Perception indicators* | *Key actors* |
|---|---|---|---|---|
| | *Process indicators* | *Outcome* | | |
| *Scientific Education*<br>*(more related to knowledge & technicalities exchange)* | • Comprehensive technical documentation (20 pages + appendix)<br>• Clear explanation of novel concepts (multi-element tokenization)<br>• Educational comparisons with existing methods (GNN, HGT)<br>• Detailed experimental setup and hyperparameters<br>• Visual aids (Figures 1-5) explaining architecture | • Enhanced technical knowledge in graph transformers<br>• Understanding of relational deep learning principles<br>• Practical skills in implementing RELGT<br>• Critical evaluation skills through ablation studies | • Clarity of technical writing<br>• Usefulness of figures and examples<br>• Accessibility to non-experts<br>• Comprehensiveness of documentation | Graduate students, Researchers, ML educators, Industry practitioners, Conference reviewers |
| *Scientific citizenship*<br>*(based on capabilities approach)* | • Open-source code release (GitHub)<br>• Use of community benchmark (RelBench)<br>• Contribution to broader RDL research agenda<br>• Addressing real-world societal challenges (healthcare, e-commerce, financial data) | • Community empowerment to use and extend RELGT<br>• Contribution to open science movement<br>• Democratization of advanced ML techniques<br>• Practical impact on enterprise data challenges | • Sense of community ownership over methodology<br>• Perceived utility for solving real problems<br>• Empowerment to contribute improvements<br>• Recognition of societal relevance | Open-source community, Industry data scientists, Healthcare researchers, Financial analysts, E-commerce platforms |

# Open Access/Open Science

| Criteria | Performance indicators (action) | | Perception indicators | Key actors |
|---|---|---|---|---|
| | Process indicators | Outcome | | |
| **Open science (reproducibility)** | • Preprint publication on arXiv (freely accessible)<br>• GitHub code repository with implementation<br>• Use of public benchmark datasets (RelBench)<br>• Detailed methodology and hyperparameters in appendix<br>• Comprehensive ablation studies (Tables 2, 6, 7, 8)<br>• Clear documentation of experimental setup | • High reproducibility of experiments<br>• Transparent research process<br>• Validation through benchmark comparison<br>• Community ability to verify results | • Confidence in research validity<br>• Trust in reported results<br>• Clarity of methodology<br>• Ease of replication | Peer reviewers, Replication researchers, ML practitioners, Conference organizers |
| **F(A)IRfication** | • Code on GitHub with clear repository structure<br>• ArXiv identifier for findability<br>• Standard data formats (RelBench benchmark)<br>• PyTorch implementation (widely used framework)<br>• Clear API and function documentation<br>• Integration with PyTorch Geometric | • Findable through GitHub and arXiv<br>• Accessible to anyone with internet connection<br>• Interoperable with PyTorch ecosystem<br>• Reusable for other relational database applications<br>• Extensible architecture for future research | • Ease of finding the research materials<br>• Accessibility across different institutions<br>• Compatibility with existing tools<br>• Utility for new applications | Repository maintainers, Package developers, ML framework teams, Research librarians |
| **Open access** | • ArXiv preprint (no paywall)<br>• GitHub repository (open-source license)<br>• Use of open datasets where possible<br>• No proprietary software requirements | • Zero-cost access to research findings<br>• Broad dissemination across institutions<br>• No barriers for researchers in developing countries<br>• Rapid knowledge transfer | • Satisfaction with access model<br>• Perceived fairness of knowledge distribution<br>• Gratitude for open sharing<br>• Support for open science principles | Global research community, Students, Independent researchers, Industry practitioners, Developing country institutions |

# Ethics

| Criteria | Performance indicators (action) | | Perception indicators | Key actors |
|---|---|---|---|---|
| | Process indicators | Outcome | | |
| **Consent as a process** | • Use of ethically-sourced benchmark datasets<br>• Respect for data usage terms from RelBench<br>• Awareness of privacy considerations in relational data<br>• Citation of original data sources | • Ethical use of public datasets<br>• Respect for data provenance<br>• Compliance with data usage agreements | • Trust in ethical data handling<br>• Transparency in data sources<br>• Responsible research conduct | Ethics review boards, Dataset curators, Data protection officers, Benchmark organizers |
| **Assent as a process** | Not Applicable | Not Applicable | Not Applicable | Not Applicable |
| **Mitigation of risk** | • Temporal-aware sampling to prevent data leakage<br>• Careful validation/test set splitting<br>• Prevention of future information in predictions<br>• No deployment of model in production (research phase)<br>• Clear documentation of limitations | • Methodologically sound research<br>• Minimized risk of misleading results<br>• Protected integrity of benchmark evaluation<br>• Responsible reporting of limitations | • Confidence in methodological rigor<br>• Trust in validity of comparisons<br>• Appreciation for transparent limitations | Peer reviewers, ML researchers, Practitioners considering adoption, Academic community |
| **Handling samples** | • Not Applicable | • Not Applicable | • Not Applicable | Not Applicable |
| **Handling Data** | • Use of anonymized/aggregated datasets from RelBench<br>• Temporal awareness to prevent information leakage<br>• Clear documentation of data preprocessing<br>• Respect for privacy in relational databases<br>• No release of sensitive intermediate data<br>• Aggregated results reporting only | • Privacy-preserving research practices<br>• Compliance with data protection principles<br>• Secure computational environment (university servers)<br>• No unauthorized data sharing | • Trust in data security measures<br>• Confidence in privacy protection<br>• Transparency in data handling<br>• Professional data stewardship | Data protection officers (Stanford, NVIDIA), IRB committees, Dataset providers, IT security teams, Research participants (original data subjects) |
| **Returning results** | • Publication of research findings through ArXiv preprint (open access)<br>• Open-source code release on GitHub for community benefit<br>• Benchmark results shared transparently (21 tasks evaluated)<br>• Comprehensive methodology documentation enabling others to apply the technique<br>• Acknowledgment of funding sources and institutional support<br>• Clear attribution to prior work and datasets used (RelBench) | • Research findings accessible to academic community, industry practitioners, and original dataset communities<br>• Practical tools (code, models) returned to community for further use<br>• Contributions to open-source ML/AI ecosystem<br>• Enhanced capabilities for organizations using relational databases<br>• Knowledge transfer enabling better data analysis in healthcare, e-commerce, finance sectors<br>• Potential improvements in services affecting data subjects (better recommendations, predictions) | • Community appreciation for open sharing of methods and code<br>• Perceived fairness in knowledge distribution<br>• Recognition of reciprocity (using public datasets, returning public tools)<br>• Satisfaction of funding agencies with public dissemination<br>• Industry and academic stakeholder value from accessible research<br>• Trust in researchers' commitment to public benefit | Original data providers (Amazon, Avito, Stack Exchange, clinical trial organizations, F1, H&M), Research community, Industry practitioners (data scientists, ML engineers), Funding agencies (NSF, Chan Zuckerberg Initiative, industry sponsors), Open-source community, End-users of applications (patients, customers, sports fans), Society at large benefiting from improved data analysis capabilities |