Project Title:
Multimodality AI-based Explainable Fall Risk Prediction in Community Home Care

Supervisors:
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Summary
The proposed PhD research explores how community home care providers can better integrate multimodal operational data and explainable artificial intelligence (AI) to enable proactive fall risk prediction. Although fall prevention guidelines emphasise systematic documentation and monitoring, current predictive approaches remain fragmented and underutilise unstructured progress notes. This research will develop a unified multimodal framework that integrates structured assessments, longitudinal visit records, and natural language representations of care notes. By combining multi-horizon survival modelling with explainable machine learning techniques such as SHapley Additive exPlanations (SHAP), the study will generate transparent, actionable risk indicators. The project aims to deliver both methodological innovation and an industry-ready decision-support framework aligned with aged care governance and safety standards.

Project Details
The proposed PhD research aims to design and validate a multimodality artificial intelligence framework for early and explainable fall risk prediction in community home care environments. Falls remain a major cause of preventable injury among older adults, and best-practice guidelines highlight the importance of proactive monitoring and documentation in community settings (Australian Commission on Safety and Quality in Health Care, 2025). However, existing risk assessment approaches are largely episodic, manual, and static.

Recent advances in AI-based fall monitoring systems have demonstrated the potential of multimodal sensing and machine learning for risk prediction (Band et al., 2025; Zhao et al., 2026). Hospital-based studies have shown promising predictive performance using structured electronic health records, yet these approaches often overlook unstructured documentation and are rarely adapted for community home care contexts. Moreover, multimodal AI models in healthcare increasingly combine text, image, audio, and structured signals (Majid et al., 2025; Zhan et al., 2024), but their integration into operational aged care systems remains limited. A critical research gap therefore exists at the intersection of multimodal data fusion (structured + unstructured + longitudinal data), explainable AI suitable for regulated care environments, and deployment-ready systems aligned with home care workflows.

This research will analyse how structured care data (mobility levels, ADLs, medication updates), incident and near-fall reports, and longitudinal visit records can be integrated with natural language processing (NLP) pipelines that extract clinically meaningful signals from progress notes. Prior work has shown that multimodal deep learning can support interpretable fall prevention strategies in smart home environments (Baek et al., 2025), and explainable AI combined with large language models can enhance risk interpretation (Luo et al., 2026). However, a unified operational framework tailored specifically to community home care remains underdeveloped.

To address this gap, the project will develop:

1. A Multimodal Data Representation Framework - Integrating structured assessments, visit-based metadata, and NLP-derived textual risk indicators.
2. Multi-Horizon Predictive Modelling - Developing models for 7-day, 30-day, and 90-day fall risk windows using: Regularised logistic regression, Explainable Boosting Models, Gradient-boosted trees with SHapley Additive exPlanations (SHAP), Discrete-time survival models
3. Explainable AI Layer - Building upon SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017), grounded in cooperative game theory, to provide both global feature importance and individual-level attribution. This ensures transparency, regulatory compliance, and human-in-the-loop validation.
4. Human-Centred Decision-Support Framework - Inspired by human-centred multimodal AI systems (Vani et al., 2025), the system will provide interpretable risk drivers and intervention-aligned recommendations suitable for care coordinators.

Key Research Questions (RQs):

- **RQ1** - To what extent do community home care organisations need to enhance the integration of structured and unstructured data for proactive fall risk prediction?
- **RQ2** - How can multimodal artificial intelligence models effectively combine structured assessments, longitudinal visit data, and progress notes to improve early fall detection?
- **RQ3** - How can explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), support transparent, actionable, and regulatorily compliant decision-making in aged care environments?

Expected Outcomes:

- A validated multimodal AI framework for fall risk prediction in community home care.
- An industry-ready decision-support prototype.
- High-impact journal publications in AI, digital health, and healthcare analytics.
- Foundations for ARC/industry collaborative translation.

Selected publications for reading

1. Australian Commission on Safety and Quality in Health Care. (2025) Preventing falls and harm from falls in Older People – Best Practice Guidelines for Community Care in Australia. **Open Access**
2. Baek J, Li Y, Lim L, Chong JW. (2025) An interpretable AI for smart homes: Identifying fall prevention strategies for older adults using multimodal deep learning. IEEE Journal of Biomedical and Health Informatics 29(10): 7643-7656.
3. Band S, Biyari M, Hsu CC et al. (2025) A review on AI approaches in elderly fall monitoring systems: Taxonomies, challenges, and open issues. Cognitive Computation 17: 176. **Open Access**
4. Majid A, Wang Y, Ali J, Ullah A, Perveen K. (2025) Multimodal LLM for

patient activity recognition: Integrating video, audio, and text in clinical environments. IEEE Journal of Biomedical and Health Informatics. doi: 10.1109/JBHI.2025.3617581

5. Zhao Q, Wu R, Chen M, Tsui K, Zhao Y. (2026) MIEF-Net: Multimodal image-enhanced fusion network for intelligent fall risk prediction. Neural Networks 195: 108260. doi: 10.1016/j.neunet.2025.108260
6. Luo J, Khani M, Adams J, Lu Q, O'Connor K, Friedland DR. (2026) Risk prediction and interpretation for fall events using explainable AI and large language models. Proceedings of the 9th International Conference on Medical and Health Informatics (ICMHI '25): 270-277. **Open Access**
7. Zhan J, Dai J, Ye J et al. (2024) AnyGPT: Unified multimodal LLM with discrete sequence modeling. Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (ACL): 9637-9662. **Open Access, https://github.com/OpenMOSS/AnyGPT**
8. Li J, Steinberg J, Li X, Yao B, Wang D, Mynatt E, Mishra V. (2024) Understanding the daily lives of older adults: Integrating multimodal personal health tracking data through visualization and large language models. Proceedings of the AAAI Symposium Series 4(1): 173-177. **Open Access**
9. Lundberg SM, Lee SI. (2017) A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems 30: 4765-4774. **Open Access**
10. Vani MS, Sudhakar RV, Mahendar A et al. (2025) Personalized health monitoring using explainable AI: Bridging trust in predictive healthcare. Scientific Reports 15: 31892. **Open Access**