How effectively did we work as a group?

Working as part of Team FinSight was a rewarding experience. Despite the challenge of balancing professional and personal commitments alongside the course, we successfully onboarded to a new business context, defined a complex analytical problem, and delivered a functional NLP and Generative AI pipeline tailored for regulatory impact; all within six weeks.

Our team dynamic worked well overall. Lauren was an excellent team lead; organised, communicative, and supportive. She set up our Discord workspace, established clear file management, defined research Qs and ensured alignment on deliverables. This structure enabled us to collaborate effectively across time zones and professional schedules. Dividing the work into four analysis streams allowed everyone to contribute code and have a tangible data science case study to showcase.

While this structure supported progress, some uneven communication occasionally slowed peer review. More synchronous collaboration between pairs would have deepened shared impact and cohesion.

How well did I perform within the group?

Personally, I was pleased with my performance and contributions. I took on a technical leadership role; setting up the GitHub repository, defining coding standards, and building the foundational datasets from raw Q&A transcripts. Once the infrastructure was in place, I focused on supporting Evasion detection and developing a Generative AI summarisation agent that synthesised outputs from topic, sentiment, and evasion models into a PRA-ready report. This gave me the opportunity to apply recent learning in LLM prompting, API integration, and model evaluation; skills directly transferable to real-world data science work.

Lauren and I collaborated closely, combining her leadership and communication strengths with my experience in remote teamwork and technical planning.

Reflecting on my own performance, I might have reduced some of the initial setup time and shifted earlier into hands-on model development, which would have left more time for experimentation with interface elements such as a Streamlit dashboard. However, I also value the structured approach I took —

ensuring the analysis aligned with the business problem before diving into implementation. It reinforced one of my core lessons from this year: measure twice, cut once.

What did I contribute?

My contributions spanned both the engineering and analytical sides of the project, from establishing data pipelines, naming conventions and peer review of the evasion detection ML, to building the summarisation agent that transformed technical outputs into supervisory insights.

This balance between technical precision and business framing was central to our success in communicating complex findings clearly and concisely for a non-technical audience.

How could we improve?

Looking ahead, I would focus on accelerating the “forming–storming–norming” process with new teams by prioritising early connection. Better attendance in the kickoff call could have improved collaboration. When team members were less responsive, progress sometimes stalled, which is an area we could have mitigated with clearer early agreements on communication expectations and escalation.

Overall, the project reaffirmed the value of structured collaboration, thoughtful planning, and applied learning. It strengthened my confidence in bridging technical data science outputs with stakeholder-ready insights; a key skill as I continue transitioning fully into a data science role.