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Holistic Neurodiversity Framework and AI-Driven Dashboard for Neurodivergent Students

by

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Project submitted as part of the requirements for
the award of
*BSc (Hons) Computing (Data and Information
Systems)*

August 2026

DECLARATION

I, Tyler Williamson declare that I am the sole author of this Project; that all references cited have been consulted; that I have conducted all work of which this is a record, and that the finished work lies within the prescribed word limits.

This work has not previously been accepted as part of any other degree submission.

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Abstract

This project addresses the systemic standardisation gap in UK higher education, where support for neurodivergent students, specifically those with co-occurring autism and ADHD (AuDHD), remains fragmented, reactive, and rigid. Despite growing adoption of the neurodiversity paradigm, static institutional adjustments fail to accommodate dynamic fluctuations in executive function fatigue, sensory overload, and routine disruptions. Consequently, autistic students in UK higher education face a 36% non-continuation rate, the highest among recorded disability groups.

To resolve this challenge, this study designs and implements the Student Support Hub: an integrated, data-driven framework and interactive proof-of-concept prototype that utilises artificial intelligence to provide tailored, low-demand support strategies for AuDHD students. Grounded in a Pragmatist philosophy and Design Science Research (DSR) methodology, the technical artefact integrates a multi-tiered architecture: an automated Python ETL pipeline unifying fragmented institutional data silos into a local Microsoft SQL Server database; a 24/7 low-stimulation canvas Power App ("Ally AI Assistant") built to WCAG 2.1 AA accessibility standards; automated cloud flow orchestration via Power Automate leveraging native AI Builder GPT capabilities; and a Microsoft Power BI analytics dashboard presenting aggregate barrier telemetry to support staff.

To enforce absolute student confidentiality and mitigate surveillance concerns, the backend implements a Privacy-by-Design architecture. Raw conversational inputs are UTF-8 binary-encoded (VARBINARY(MAX)) and decoupled from identity tables, ensuring staff view macro-level barrier metrics without accessing private conversations. Furthermore, an institutional cryptographic attestation framework generates verifiable credentials to ensure support data portability across post-16 transitions into employment.

Empirical evaluation combining an internal technical protocol audit (N=5) and an external stakeholder survey (N=11) demonstrated exceptional concept viability (4.82/5.00) and high visual sensory comfort (4.09/5.00). While surfacing version 1.0 proof-of-concept limitations in state handling and prompt context binding, the results validate that combining low-demand conversational AI with automated telemetry offers a scalable blueprint for reducing executive load, improving retention, and dismantling support cliff-edges for neurodivergent adults.

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Chapter 1 – Introduction

1.1 Chapter Introduction

The landscape of higher education is currently navigating a significant transition in how it understands and supports cognitive difference. Central to this change is a transition away from clinical deficits models toward the neurodiversity paradigm, which recognises conditions such as autism and Attention Deficit Hyperactivity (ADHD) AS natural variations of human neurology. However, despite theoretical progress, institutional support structures remain fragmented and reactive,

This creates a severe standardisation gap for students with co-occurring autism and ADHD (AuDHD), particularly during the critical transition into higher education and post-16 independence, a transition frequently described as a support "cliff-edge". Traditional accommodations, such as static extra time in examinations, fail to account for the fluctuating interplay between executive function fatigue, sensory overload, and academic pressure. In the UK, autistic higher education students face a 36% non-continuation rate, the highest among all recorded disability groups. This disparity underscores the urgent need for flexible, proactive, and privacy-preserving support infrastructures.

1.2 Project Description

This project proposes a holistic, AI-driven digital framework designed to bridge the gap between rigid institutional systems and the dynamic needs of AuDHD learners. The solution integrates disparate university data streams, such as academic timetables, administrative adjustments, and real-time student self-reports, into an ethically governed, unified data architecture.

The core solution consists of a multi-tiered architecture:

- The Input and Interaction Tier: A low-stimulation canvas app ("Ally AI Assistant") built to WCAG 2.1 AA standards that enables 24/7 natural language chat interaction.
- The Intelligence and Data Tier: An automated Extract, Transform, Load (ETL) pipeline and cloud orchestration flow that anonymises conversational inputs into structured severity tokens.

- The Analytics Tier: An interactive Microsoft Power BI dashboard that translates aggregate barrier metrics into visual scaffolding for institutional support staff without compromising individual student privacy.

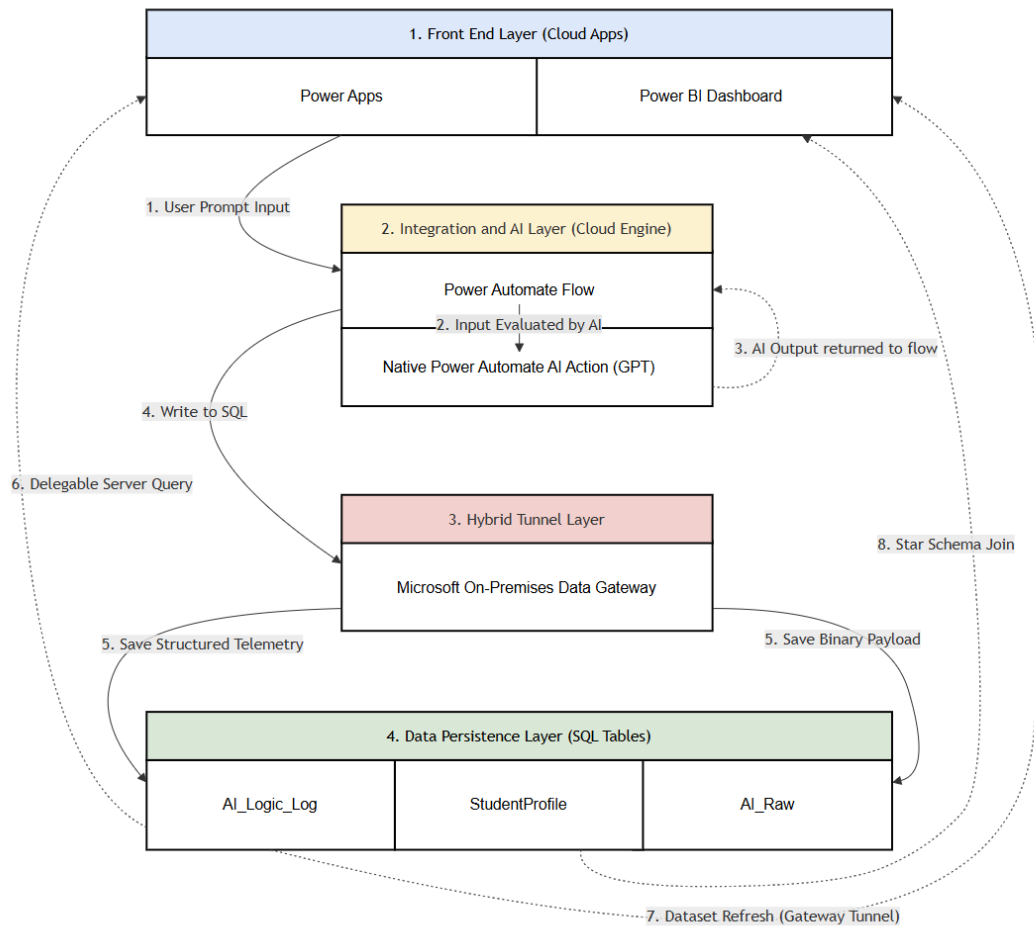


Figure 1: High-Level Conceptual System and Architecture Data Flow

1.3 Project Aim and Objectives

1.3.1 Project Aim

To research, design, and develop an integrated, data-driven framework and interactive proof-of-concept dashboard prototype that utilises AI to provide a tailored, low-demand support strategies for AuDHD students in higher education.

1.3.2 Project Objectives

To achieve this aim, the project is structured across five core work packages:

- **Synthesise:** Critically investigate the cognitive, sensory, and administrative barriers faced by AuDHD students to establish the requirements for a holistic support framework.
- **Architect:** Engineer a synthetic dataset and an automated ETL pipeline to unify fragmented institutional data silos into a decoupled SQL schema.
- **Develop:** Configure and tune an AI conversational workflow capable of parsing student inputs and generating low-friction support strategies.
- **Create:** Design and build an accessible canvas app and a Power BI analytics dashboard to display real-time barrier insights for students and staff.
- **Evaluate:** Conduct a dual-track technical protocol audit and external stakeholder evaluation to assess system performance, accessibility, and concept viability.

1.4 Structure of the Report

This report is organised into seven sequential chapters:

- **Chapter 2 – Research and Literature Review:** Evaluates the neurodiversity paradigm, current higher education support models, data integration ethics, and assistive AI design principles.
- **Chapter 3 – Research and Design Methodology:** Justifies the Design Science Research (DSR) methodology, Pragmatist philosophy, and Rapid Application Development (RAD) lifecycle.
- **Chapter 4 – Design and Implementation:** Details the technical build, including the SQL relational schema, Python ETL scripts, Power Automate cloud flows, Power Apps canvas interface, and Power BI semantic model.
- **Chapter 5 – Evaluation:** Presents empirical results from internal technical testing (N=5) and external stakeholder surveys (N=11), including a full SWOT analysis and proof-of-concept assessment.

- **Chapter 6 – Conclusions and Recommendations:** Summarises core contributions, links outcomes to project aims, and details a phased three-stage future roadmap.
- **Chapter 7 – Reflection:** Reflects upon technical obstacles, soft skill development, academic learning, and retrospective improvements.

By synthesising the core requirements of a holistic support framework from literature and operationalising them through an ETL pipeline, low-stimulation chat interface, and Power BI dashboard, this project demonstrates how data-driven interventions can move beyond reactive metrics toward proactive, collaborative scaffolding. This comprehensive approach ensures the resulting framework is not merely a technical artefact, but a viable blueprint for fostering inclusive success in higher education.

Chapter 2 – Research and Literature Review

2.1 Chapter Introduction

This chapter provides a comprehensive review of scholarly literature and technical research underpinning the Student Support Hub. It establishes the theoretical foundation of the neurodiversity paradigm and examines the specific, co-occurring challenges faced by AuDHD students in higher education. It critically evaluates current institutional support structures, identifying the standardisation and data silo gaps that drive high non-continuation rates. Furthermore, the chapter reviews learning analytics, predictive AI, ethical governance, and inclusive design principles, before systematically evaluating database, programming, and visualisation technologies. Finally, it synthesises these research findings into actionable design decisions for the proof-of-concept prototype.

2.2 Neurodiversity and AuDHD in Higher Education

2.2.1 Introduction

The landscape of higher education is currently navigating a significant transition in how it understands and supports cognitive difference. Central to this change is a move away from viewing conditions like autism and ADHD as clinical deficits, instead recognising them as part of a broader spectrum of human neurology. This section explores the foundational principles of the neurodiversity paradigm and examines the specific, often contradictory challenges faced by students with a co-occurring profile of autism and ADHD, known as AuDHD. By analysing the lived experiences of these students within the UK university system, this section identifies critical gaps in current support structures, establishing why traditional, static interventions are insufficient and creating a clear necessity for flexible, proactive AI scaffolding.

2.2.2 The Neurodiversity Paradigm and Key Terms

The neurodiversity paradigm fundamentally reimagines cognitive variation as a natural dimension of human diversity rather than a collection of disorders requiring remediation or normalisation [1][2]. This perspective directly challenges the dominant medical model, which pathologises divergence as a series of deficits to be treated or cured.

In contrast, the social model of disability emphasises that the environment, rather than the individual, creates barriers to success. Crucially, concepts such as double empathy (the mutual misunderstanding between different neurotypes) and autistic masking (the exhausting process of suppressing traits to fit in) are central to understanding the modern student experience [1][3][4]. Currently, UK higher education adoption of this paradigm is uneven; many institutions still frame neurodivergence as a barrier to be overcome rather than a variation to be accommodated [3].

2.2.3 AuDHD Characteristics and Lived Experiences

AuDHD exemplifies the complexity of neurodiversity by combining traits that pull a student in opposite directions. The autistic need for predictability frequently clashes with ADHD-driven impulsivity and novelty-seeking. This internal tug-of-war results in a unique state of chronic exhaustion known as AuDHD burnout [5].

Dimension of Experience	Impact on the AuDHD Student
Cognition Conflict	The internal struggle between a need for routine and a drive for novelty causes intense mental fatigue.
Executive Function	Challenges with time perception and prioritisation make traditional academic deadlines a major source of anxiety.
Social Navigation	The pressure to "mask" traits to fit in leads to chronic exhaustion and a sense of social isolation.
Sensory Regulation	Environments like lecture halls often function as sensory assaults, hindering information processing.

Table 1: Experiences and the impact on the AuDHD student

Lived experiences in the UK reveal that students engage in pervasive masking to meet neurotypical expectations, leading to attrition rates significantly higher than their peers [6]. Lecture halls function as sensory assaults and group projects as social minefields [7][8]. Flexible, unstructured university schedules fail to meet the autistic need for routine while simultaneously triggering ADHD procrastination cycles [8][9].

2.2.4 Implications for Learning, Wellbeing, and Support Needs

These characteristics profoundly disrupt academic engagement. Autistic students face a 36% non-continuation rate, the highest among all recorded disability groups in the

UK [10][11]. his disparity is driven not by academic inability, but by the increased cognitive burden of the student acting as their own case manager [12]. Beyond attrition, 80% report significant psychological distress, 71% struggle with anxiety, and 47% with depression, exacerbated by fragmented support services and fear of stigma [13]. Current support models remain too rigid; static exam accommodations fail to address dynamic, fluctuating daily needs.

2.2.5 Conclusion

In summary, the transition toward a neurodiversity-informed approach in higher education highlights a persistent mismatch between institutional expectations and neurodivergent realities. AuDHD students face a unique set of challenges characterised by internal cognitive conflict and the exhausting requirement of social masking. While university policies may aim for inclusion, the practical application of support remains fragmented. The standardisation gap identified here reinforces the argument that traditional, static adjustments are no longer adequate. Moving forward, the focus must shift toward intelligent, adaptive support systems. This establishes the foundation for the AI-driven framework proposed in the following chapters, which seeks to provide the real-time scaffolding necessary for both academic success and personal wellbeing.

2.3 Current Support Models and the Limitations

2.3.1 Introduction

While student support in higher education is described as comprehensive, a neurodiversity-informed perspective reveals a system that is fragmented, reactive, and standardised. Support is distributed across separate academic, disability, and wellbeing services that rarely communicate or share data. This section evaluates how current UK policy and existing digital strategies fail to bridge the "Standardisation Gap" for neurodivergent learners.

2.3.2 Policy Context

The institutional standardisation gap is increasingly recognised as a key driver of workforce transition failures:

- **The Buckland Review:** Highlights that only 36% of autistic graduates find full-time employment within 15 months due to unintegrated university support [14][15].

- **The Equality Act and DSA:** Relies on static, tick-box adjustments through the Disabled Students' Allowance (DSA), failing to account for daily executive or sensory fluctuations.
- **National Autistic Society (NAS) Goals:** Advocate for environmental design and holistic support pathways rather than medicalised accommodations [16][17][18].
- **Institutional Alignment (UWTSD Strategic Plans):** Commits to digital transformation and personalised pathways to improve retention, providing the strategic mandate for this project [19]. (See Appendix A)

2.3.3 Student Support Structures and Fragmentation

Student support exists as a patchwork of services (academic advising, disability support, counselling) operating with isolated mandates and information systems [20]. For AuDHD students, this separation is artificial. Executive functioning, sensory regulation, and mental health interact continuously with academic performance. Forcing students to navigate multiple front doors creates an unsustainable administrative and emotional tax [21][22].

Disability services rely on formal adjustment plans triggered by diagnostic proof, resulting in standard packages (e.g. extra exam time) secured through burdensome bureaucratic labour [6][23]. Established at enrolment, these plans assume static needs, whereas AuDHD requirements oscillate between routine and flexibility within the same semester [2][22].

2.3.4 One Size Fits All Adjustments and Data Silos

Standardised models group students into broad diagnostic categories, simplifying administration at the expense of individualised care [24][10]. Standard menus fail to tackle daily friction points like laboratory sensory overload or VLE system fragmentation [25][5][10]. Crucially, autism and ADHD are siloed, ignoring co-occurrence conflicts [26]: autistic plans prioritise predictability and rigid routine, while ADHD advice stresses novelty and stimulation. AuDHD requires both [22][27].

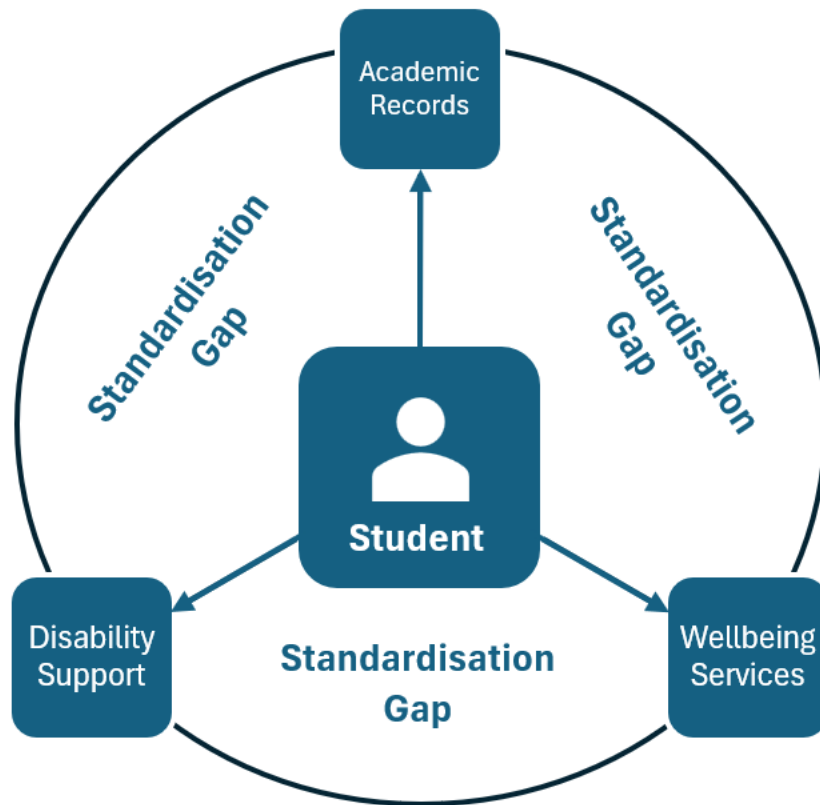


Figure 2 - The fragmentation of institutional data silos and the resulting administrative burden on the student

With only 40% of neurodivergent students disclosing their status, largely because 66% mask daily to fit into standard systems, burnout risks reach 70% [10][28]. The financial cost to institutions is severe (£25,000-£35,000 per dropout [13]), accompanied by a persistent degree outcome gap.

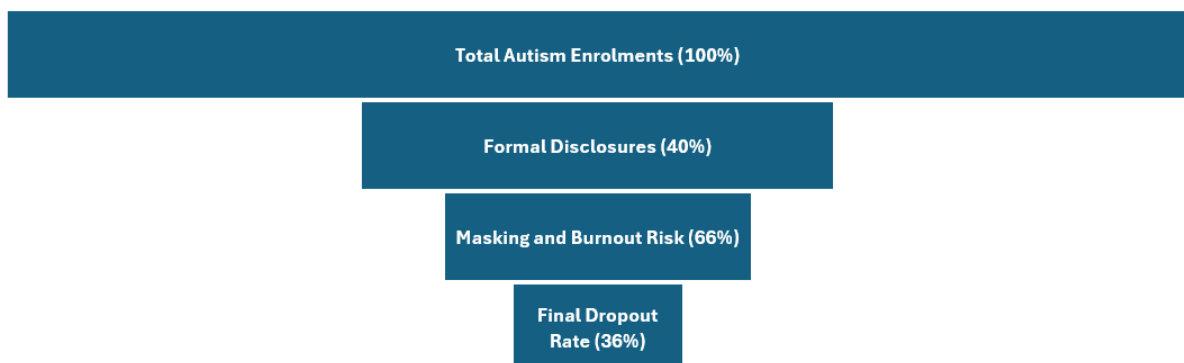


Figure 3 - Cumulative impact of non-disclosure and masking on student retention

2.3.5 Digital Support Case Studies

Recent UK and international initiatives demonstrate the potential of digital tools while highlighting integration gaps:

Initiative / Tool	Approach and Strengths	Identified Limitations and Integration Gap
A-Skills Programme [28]	Online study/life skill platform co-designed with autistic students.	Purely online delivery struggled with student relatedness; required manual facilitator intervention.
EPIC Toolkit [29]	Psychoeducation and strategy pairing (chunking, mind-maps).	Successful in home/school pilots; lacks integration into higher education institutional analytics.
Access Transitions [30]	Evaluated Level 1 system transitions and recursive support needs.	Highlighted system mismatches; support remains non-linear and poorly integrated into degree systems.
Participatory Support [31]	Exam adjustments and mentoring evaluation.	Support relies on individual staff goodwill rather than automated institutional frameworks.
Autism&Uni Toolkit [32]	Static digital toolkit for university transition orientation.	Lacks real-time data integration to adapt to fluctuating degree challenges. (See Appendix A)

Table 2: Initiatives or Tools Strengths and Limitations

Current interventions remain standalone portals. Addressing systemic attrition requires moving beyond manual portals toward a unified, proactive data integration engine.

2.3.6 Conclusion

In summary, current student support in higher education functions as a reactive and standardised ecosystem that inadvertently privileges students who are already able to advocate for themselves. While digital interventions such as the A-Skills programme and the EPIC toolkit demonstrate the potential for adaptive skill-building, they remain standalone solutions that lack integration into broader institutional data architectures. For AuDHD learners, this fragmented landscape creates a system mismatch during critical transitions, forcing them to navigate disconnected silos of support while managing an increased cognitive burden [2][22]. Addressing these gaps built into the very architecture of current systems, requires a fundamental rethink of data integration. Interventions must move beyond manual, reactive portals toward a model

that is holistic, personalised, and proactive. This conclusion justifies the development of the AI-driven framework explored in the following chapters, which is designed to bridge the standardisation gap by fusing disparate data silos into a unified, real-time support engine.

2.4 Data and AI for Student Support in Higher Education

2.4.1 Introduction

Data-driven approaches in higher education now underpin student support activities, from predicting academic risk to tailoring feedback and resources. Learning analytics and artificial intelligence promise targeted interventions, yet their current use largely reflects institutional performance priorities, overlooking the fluctuating support needs of AuDHD learners [25][33][34][35].

2.4.2 Learning Analytics and Early Warning Systems

Learning analytics uses VLE logs and clickstream metrics to model engagement and predict grades [33][35][36]. Early Warning Systems (EWS) flag individuals based on low login frequency or late submissions [34][37]. However, most models optimise for coarse academic outcomes (final grades) rather than student experience [34][35]. Nuanced indicators of executive function fatigue, sensory overload, or mental wellbeing are absent [36]. For neurodivergent students, clickstream models generate generic risk labels that pathologise divergence without providing actionable support.

2.4.3 Institutional Data Landscapes and AI Tools

Current analytics initiatives draw on narrow performance datasets, ignoring siloed disability and counselling records due to confidentiality constraints [33][34][36]. AI powers administrative chatbots and Student Relationship Management (SRM) communication workflows [38][37][39]. Yet, these tools assume a generic student archetype. Automated outreach can be experienced as intrusive by neurodivergent learners, while predictive algorithms risk introducing algorithmic bias against disabled cohorts [25][40][41][42]. Projects like Oxford's NESTL initiative validate that combining AI with neurodiversity frameworks represents the cutting edge of educational technology [43][44].

2.4.4 Synthesis: Potentials and misalignments

AI provides scalable analytics infrastructure, but three primary misalignments exist for AuDHD support:

1. **Feature Mismatch:** VLE "clicks" fail to capture sensory saturation or executive initiation blocks [33][35].
2. **Granularity Mismatch:** Analytics evaluate individual courses rather than whole-person wellbeing trajectories [25][34].
3. **Intervention Mismatch:** Automated outreach is uncalibrated by neurotype, risking alienating users [42][45].

2.4.5 Conclusion

For an AuDHD-centred framework, existing AI work must be repurposed and extended. Predictive models must be reframed around individual, dynamic support profiles rather than static risk scores. Using synthetic data to model such profiles explores how institutional data can be reorganised into a holistic system where neurodivergent students are central design partners [25][38][35][39].

2.5 Ethical and Responsible AI for Student Support

2.5.1 Introduction

As data-driven systems become embedded in higher education, ethics, privacy, and responsibility have moved to the centre of academic debate. Early implementations treated ethics as secondary compliance, but AI-driven support raises deeper concerns regarding surveillance, autonomy, fairness, and trust [46][47]. For AuDHD students, ethical AI principles are foundational design constraints [48].

2.5.2 Key Ethical issues in Educational Analytics

Behavioural tracking often occurs without meaningful student consent, creating a "Fitbit for learning" atmosphere that blurs support with monitoring [49][50]. Black-box predictive models compound these risks by coding disability status as an opaque risk factor, reinforcing social stigma [48][50][51].

2.5.3 Responsible AI Principles for Student Support

Responsible AI frameworks demand fairness, transparency, data minimisation, and human oversight [46][47][49]. Systems must avoid function creep, ensuring learning

data is never repurposed for disciplinary control. Implementing human-in-the-loop workflows guarantees that AI algorithms generate supportive recommendations while human staff retain final interpretative responsibility [47][48].

2.5.4 Implications for Framework Design

For an AuDHD-centred framework, care and justice commitments dictate three key practices:

1. **Synthetic Data Usage:** Utilising parameterised synthetic datasets for proof-of-concept testing to eliminate real-world privacy exposure [46][52].
2. **Interpretable Profile Logic:** Replacing opaque risk scores with clear, profile-based barrier vectors [48][50].
3. **Granular Student Optionality:** Ensuring students maintain full agency over data sharing preferences without penalty [51].

2.5.5 Conclusion

Overall, the ethics of data-driven support depend on whether systems deepen or erode trust and autonomy. By foregrounding privacy-by-design, transparency, and human oversight, the proposed framework positions itself within a care-centred strand of AI in education [47].

2.6 Designing AI for Neurodivergent Learners

2.6.1 Introduction

Digital tools are positioned to increase accessibility, yet design frequently assumes a generic student archetype, failing to account for AuDHD profiles. Assistive technology research shows thoughtfully designed tools addressing sensory, cognitive, and executive needs significantly enhance autonomy [53][54][55]. However, this work remains fragmented across inclusive design and educational AI literature [25][56].

2.6.2 Assistive Technology and Human-Centred Principles

Assistive technology research demonstrates that tools tailored for cognitive offloading (checklists, visual timelines) and customisable sensory loads enhance self-efficacy [54][55][57][58]. Conversational interface design is validated by the W3C Cognitive Accessibility Gap Analysis, which identifies complexity barriers in standard VLE layouts [59][60]. Adopting Microsoft's Inclusive Design philosophy ("Solve for One,

Extend to Many") utilises complex AuDHD requirements to build an accessible platform for all students [61].

2.6.3 Dynamic Modelling and Synthetic Data Strategy

Because AuDHD needs fluctuate dynamically over time, static tags are inadequate [25][62]. Using parameter-driven synthetic datasets enables researchers to model complex state streams (burnout trajectories, hyperfocus cycles) and evaluate AI logic safely without processing real student records [56][63][64][65].

2.6.4 Conclusion

Designing AI for neurodivergent learners requires integrating assistive technology insights, neurodiversity-affirming pedagogy, and human-centred AI principles. This synthesis directly informs the architectural choices of the developed prototype, keeping technical decisions grounded in evidence-based understanding [25][53][56].

2.7 Holistic Neurodiversity Framework (Proof of Concept)

2.7.1 Introduction

Research points toward a holistic, proactive framework rather than fragmented systems, conceptualising students within interacting systems of people and technologies [66][67][68]. Drawing on Ecological Systems Theory, student success depends on interactions across micro-systems (classrooms) and macro-systems (institutional policies) [69].

2.7.2 Five Core Framework Requirements

1. **Integrated Data Fusion:** Unify academic, wellbeing, and access records via an ETL pipeline to distinguish effort deficits from cognitive fatigue proxies [65][66][67][70].
2. **Dynamic State Modelling:** Represent fluctuating neurodivergent states (burnout, hyperfocus) rather than static adjustment lists [67][68][69].
3. **Proactive Heuristics:** Use analytics to identify early difficulty markers, initiating supportive human outreach [69][71].
4. **Agency-First Logic:** Present AI strategies as collaborative options, empowering the student as an active partner [27][72].

5. **Ethical Governance and Conversational Scaffolding:** Enforce privacy-by-design while deploying conversational agents to remove social performance and masking [64][73][74][75].

2.7.3 Conclusion

Transitioning to a holistic, proactive framework requires shifting institutional mindsets and technical architectures. Grounding the model in ecological systems theory acknowledges that AuDHD student success depends on dynamic interactions between profiles, environments, and support networks. These core requirements serve as the blueprint for the developed prototype.

2.8 Technical Tool Evaluation

To realise an adaptive framework balancing real-time scaffolding with robust privacy, the software stack is evaluated across three core operational layers:

2.8.1 Data Management Layer

Tool	Pros	Cons	Fit for Framework
SQL Server [71]	- Highly structured. - Robust ER Integrity. - Optimal for complex relational Queries.	- Requires predefined schemas. - Rigid if data types shift rapidly.	Essential: Solves siloed data problems by fusing academic and sensory tables with precise indexing.
Oracle [76]	- High enterprise security. - Massive institutional scalability.	- High licensing costs. - Overly complex for a PoC.	Unnecessary: Introduces excess overhead for this development stage.
PostgreSQL [77]	- Extensible architecture - Native JSON support - Concurrent asynchronous I/O.	- Requires manual performance tuning - Lacks native Microsoft low-code UI tooling.	Partial: Advanced open-source engine but lacks native Power Platform integration.
MongoDB (NoSQL) [78]	- Document-oriented. - Dynamic schema flexibility. - Horizontally scalable.	- Lacks native foreign key constraints - Risk of data inconsistency.	Rejected: Loose NoSQL relationships introduce architectural risk.

Table 3: Evaluation of Data Management Technologies

2.8.2 Processing and Logic Layer

Language	Pros	Cons	Fit for Framework
Python [79]	- Rich NLP/ML ecosystem. - Lightweight execution for custom heuristics.	Slower execution speed than compiled C++.	Industry Standard: Optimal for data cleaning, ETL pipelines, and binary privacy transformation.
C++ [80]	- Ultra-high machine execution speed. - Direct memory management	- Verbose syntax - Memory-unsafe if unmanaged. - Lacks native data science libraries.	Rejected: Verbose syntax and lacks rapid data manipulation libraries.
Power Automate [81]	- Visual drag-and-drop workflows. - Native enterprise API connectors.	- Restricted to linear logic. - Inefficient for complex multi-conditional math.	Selected (Integration): Excellent for simple event triggers and API routing; paired with Python for heavy logic.
Java [82]	- High-performance multithreading. - Strict type-safety.	- Verbose boilerplate code. - Object-oriented overhead.	Rejected: Introduces unnecessary syntactic overhead for text/array processing.

Table 4: Evaluation of Processing and Logic Languages

2.8.3 Visualisation and Application Layer

Tool	Pros	Cons	Fit for Framework
Power BI [83]	- Native relational data modelling. - Dynamic chart deployment. - Seamless Power Platform UI integration.	UI layouts bound to Power BI grid constraints.	Selected: Superior ability to transform SQL datasets into scannable visual information.
Tableau [84]	- Advanced aesthetic customisation. - Deep exploratory data analytics.	- Steeper learning curve - Weaker native low-code app integration.	Rejected: Lacks low-code ecosystem agility for direct user-interaction layers.
Power Apps [85]	- Bidirectional interaction. - Native WCAG 2.1 AA framework. - Direct chatbot integration.	Limited advance data visualisation out-of-the-box.	Selected: Handles the user-input layer and chatbot interface, feeding SQL and Power BI.
React / JS [86]	- Absolute UI customisation. - Lightweight client-side rendering	Requires manual development of auth tokens, database APIs, and WCAG compliance.	Rejected: Building WCAG and security infrastructure from scratch introduces excessive time overhead.

Table 5: Evaluation of Visualisation and Application Tools

2.8.4 Conclusion

In summary, evaluating the technical ecosystem confirms that a hybrid stack combining SQL Server, Python, Power Automate, Power Apps, and Power BI offers the optimal balance between strict relational integrity, rapid algorithmic processing, WCAG 2.1 AA accessibility compliance, and low-demand visual presentation. This technical selection addresses the data silo and administrative tax problems identified in literature while maintaining strict Privacy-by-Design boundaries.

2.9 Synthesis: Turning Research into Design Principles

This section completes the literature review by mapping research findings to technical design decisions.

Research Findings (The "Who and What")	Future Work Suggestions	Project Design Decisions (The Build)
Siloed Data: Institutional data is fragmented across services [20].	Integration of cross-domain data into holistic profiles [9][87].	Decision: Build an ETL pipeline to unify synthetic academic and wellbeing data.
Executive Load: Neurodivergent Students struggle with complex administrative processes [21].	Human-centred AI that simplifies access to support.	Decision: Implement a Conversational Bot as the primary interface to allow for natural language inputs.
Static Support: Accommodations fail to address daily fluctuations [6][22].	Real-time, adaptive scaffolding responding to fluctuation [67].	Decision: Use AI logic to suggest dynamic support strategies based on weekly states.
Masking Burden: Students act as their own case managers [6][21].	Empowering students through agency and partnership [2][6].	Decision: Create a dashboard acting as a collaborative "shared view" for staff and students.
Opacity and Trust: "Black Box" AI models cause student anxiety [46].	Explainable AI (XAI) providing transparent reasoning.	Decision: Prompt the AI model to explain why it is suggesting a specific intervention.
Transition Gap: Only 36% of autistic graduates find full-time work [14].	Focus on environmental design and employer readiness.	Decision: Include transition readiness metrics to teach long-term self-advocacy skills.

Table 6: Mapping Research Findings to Project Design Decisions

2.10 Chapter Conclusion

In conclusion, this chapter has critically evaluated the literature surrounding neurodiversity, AuDHD higher education experiences, institutional data silos, ethical AI governance, and low-stimulation software design. By synthesising these findings, the chapter established the five core requirements for a holistic framework and justified the selection of a Microsoft Power Platform, SQL Server, Python, and Power BI technology stack. These theoretical insights and technical choices directly inform the Design Science Research methodology, data engineering strategy, and software architecture detailed in Chapter 3.

Chapter 3 – Research and Design Methodology

3.1 Chapter Introduction

This chapter outlines the methodological framework used to evaluate and construct the Holistic Neurodiversity Framework and technical artefact. By applying Saunders' Research Onion, the chapter justifies the progression from foundational philosophical principles to a practical Design Science Research (DSR) strategy [88][89]. It details the software engineering lifecycle, the synthetic data strategy across six neurodivergent dimensions, the system's technical architecture, and tool stack selections (Power Apps, SQL Server, Python, and Power BI). This approach ensures that the resulting technical proof of concept (PoC) is grounded in empirical evidence and institutional reality, bridging theoretical AuDHD clinical research with low-code software engineering.

3.2 Research Methodology

The research design is structured through the following nested layers of the Research Onion:

3.2.1 Research Philosophy: Pragmatism

This project adopts a Pragmatist philosophy. In computing research, Pragmatism asserts that the most important determinant of the research is the problem being solved [88]. Here, the 36% attrition rate of AuDHD students is the focal point. Pragmatism justifies the creation of a technical Artefact (the AI-driven dashboard) as a valid form of knowledge, prioritising a workable solution to the standardisation gap over abstract theoretical debate [90].

3.2.2 Research Approach: Abduction

The project utilises an Abductive approach. This allows for a continuous movement between the theoretical "Knowledge Base" of neurodiversity and the practical build of the framework [91]. Abduction is essential for identifying patterns in Synthetic Data that do not fit traditional neurotypical models, allowing the AI logic to be refined iteratively.

3.2.3 Research Strategy: Design Science Research (DSR)

Design Science Research (DSR) is the primary strategy for this computing project. Unlike traditional research that seeks to describe the world, DSR aims to change it by developing innovative artefacts to solve complex problems [92]. The project follows the DSR Cycle [89]:

- **Problem Identification:** The systemic failure of siloed, reactive support.
- **Definition of Objectives:** Establishing the 5 Core Requirements for a Holistic Framework.
- **Design and Development:** The engineering of the ETL pipeline and the Conversational AI.
- **Demonstration:** Testing the system resilience through Synthetic Student Personas.

3.3 Design Methodology

The Design Methodology details the software engineering lifecycle used to construct the framework layers.

3.3.1 The Synthetic Data Strategy

To provide a 360-degree view of student success and wellbeing without risking real student privacy, the dataset is engineered across six core dimensions of neurodivergent experience:

1. **Executive Function:** Tracking task initiation lag reported via the chatbot.
2. **Cognitive Switching:** Parsing timetable density to infer transition fatigue across physical locations and delivery modes.
3. **Sensory Saturation:** Simulating environmental stressors (lighting, acoustics, crowd density) to identify hostile learning environments.
4. **Affective and Social Battery:** Tracking real-time cues of anxiety, rejection sensitivity (RSD), and high-stakes social interactions (mandatory group presentations) that drive masking and subsequent withdrawal.
5. **Hyperfocus Cycles:** Detecting periods of extreme deep work that risk basic need neglect and burnout.
6. **Submission Velocity:** Measuring engagement shape (steady workflow vs 12-hour dopamine-driven crunch).

(See Appendix C)

3.3.2 Technical Architecture

The practical build is divided into three functional layers that transform raw institutional data and private student dialogue into a unified, neuro-affirming support system:

- **The Data Layer (Architect):** An ETL (Extract, Transform, Load) Pipeline built in Python. This layer unifies fragmented university data silos into a single, cohesive SQL Database Schema, integrating Academic Lifecycle Data and Administrative Adjustments (e.g. differentiated deadlines, DSA status).
- **The Intelligence Layer (Develop):** A 24/7 LLM-driven Conversational Agent tuned via prompt engineering to act as a neuro-affirming peer. It parses student stress inputs, identifies burnout markers against upcoming deadlines, and anonymises raw text into high-level Severity Tokens (e.g. 7/10 Task Initiation Block).
- **The Interface Layer (Create):** A Power BI Interactive Dashboard designed using Microsoft Inclusive Design principles. It translates AI logic and institutional markers into a "Shared View" for students and staff, enabling curricular management across wider cohorts without exposing private conversations.
- **Data Entities:** The SQL schema is structured into four primary entities: Student_Profile, Institutional_Context (Timetables/Deadlines), Affective_Tokens (anonymised cues), and Intervention_History (AI-advised strategies).

3.3.2.1 Operational Workflow

When a student reports overwhelm via the Power App front-end, the Intelligence Layer cross-references this with Extended Deadlines in the SQL Data Layer. If a conflict is found, the Interface Layer (Power BI) triggers a high-severity alert for the student support officer.

3.3.3 Data Relationship and Entity Framework (ERD)

To facilitate the Anonymising Buffer, the SSMS backend utilises a relational schema. The Student_Profile entity remains decoupled from Affective_Tokens through a unique anonymised identifier. This ensures that while the Intelligence Layer pulls Academic Lifecycle Data (e.g. Differentiated Deadlines) for context-aware support, raw conversational text is never presented alongside a student's legal identity.

3.3.4 The Technical Development Stack

The project adopts a Rapid Application Development (RAD) approach to move from conceptual design to a functional Proof of Concept (PoC), bypassing static UI prototyping to allow front-end assembly to happen concurrently with backend logical integration:

- **Frontend and Input Layer (Power Apps):** Low-code environment selected for the 24/7 chatbot interface due to built-in WCAG 2.1 AA accessibility frameworks, avoiding the development timeline and compliance risks of bespoke React builds.
- **Data Management Layer (SSMS / SQL Server):** Hosts the Unified SQL Schema. Selected over NoSQL (MongoDB) due to strict foreign key enforcement and ACID compliance needed to securely decouple identity from telemetry tables.
- **Logic and Pipeline Layer (Python via VS Code):** Selected for the automated ETL pipeline and custom heuristics due to its rich data science ecosystem (pandas, sqlalchemy) and rapid prototyping agility.
- **Visual Scaffolding Layer (Microsoft Power BI):** Connects to SQL Server to display cohort macro-analysis and student-facing indicators, selected for its relational data-modelling engine and native Power Platform interoperability.

3.4 Methodology Synthesis Summary

Research Onion Layer	Project Choice	Technical Justification
Philosophy	Pragmatism	Prioritises the development and evaluation of a functional, technical Proof of Concept (PoC) as the primary vehicle to solve institutional attrition and the graduate employment gap.
Approach	Abductive	Moves iteratively between established AuDHD clinical theory (the Internal Tug-of-War) and active Python/SQL data engineering to develop responsive heuristics.
Strategy	Design Science Research (DSR)	Provides a structured, academically rigorous framework for the iterative software development, deployment, and validation of an innovative IT artefact.
Design Model	Rapid Application Development (RAD)	Bypasses traditional static design tools by utilising Microsoft Power Apps for direct frontend user interface assembly. This allows for concurrent layout refinement and native WCAG 2.1 AA accessibility checking.
Data Choice	Synthetic/Relational Simulation	Utilises a parameter-driven synthetic dataset engineered across six dimensions of neurodivergent experience. This guarantees absolute ethical governance, data minimisation, and "Privacy-by-Design" testing.
Evaluation	Requirements Based (KPI & Protocol)	Evaluates the PoC's algorithmic precision, user agency, and ethical alignment using internal technical testing and external stakeholder evaluation.

Table 7: Synthesis of Research Onion Layers and Technical Choices

3.5 Chapter Conclusion

In conclusion, this chapter has outlined and justified the methodological framework underpinning the Student Support Hub. By grounding the project in a Pragmatist philosophy, an Abductive approach, and a Design Science Research (DSR) strategy, the methodology bridges clinical AuDHD theory with practical computing engineering. The implementation of a Rapid Application Development (RAD) lifecycle and a synthetic data strategy ensures ethical compliance and rapid iteration across Power Apps, SQL Server, Python, and Power BI. These research and engineering frameworks provide the structural foundation for the implementation details presented in Chapter 4.

Chapter 4 – Framework and Artefact Implementation

4.1 Chapter Introduction

This chapter details the engineering design decisions and technical implementation of the Student Support Hub. It describes how institutional support policies are operationalised into an automated, active codebase across three integrated tiers: Data Ingestion (SQL Server and Python ETL), Cloud Orchestration (Power Automate and On-Premises Data Gateway), and User Presentation (Power Apps Canvas and Power BI Analytics). The chapter examines the relational schema topology, privacy-by-design encryption mechanisms, server-side query delegation, and integrated ecosystem architecture that collectively eliminate administrative friction for neurodivergent learners.

4.2 Overview and System Requirements

The primary goal of the design phase is to translate the five core requirements identified in Chapter 2 (Integrated Data Fusion, Dynamic State Modelling, Proactive Heuristics, Agency-First Logic, and Ethical Governance) into a functional IT artefact. The system addresses the systemic standardisation gap by replacing static, paper-based accommodation forms with an active, data-driven support engine.

4.3 Digital Strategy for Holistic Support

4.3.1 Operationalising Support Policy into Code

The digital strategy transitions static accommodation forms into an active, querying codebase. Instead of treating adjustments as immutable PDF documents, the framework establishes a relational database model where student support structures are codified directly into the SQL schema. The system queries central student information tables natively, mapping variables like differentiated deadlines, funding status, and module configurations straight to an active user profile. This computational strategy eliminates manual departmental data handling, ensuring institutional policy is executed automatically via backend data states.

4.3.2 Architecture Tiers and Ecosystem Integration

The strategy eliminates administrative tax by deploying an interconnected, low-latency software stack where information flows natively without custom API middleware. The architecture is split across three functional tiers:



Figure 4: Ecosystem Overview

- **The Input Layer (Power Apps):** Provides a direct user interface featuring native WCAG 2.1 AA compliance hooks. Students interact with a 24/7 conversational assistant ("Ally AI Assistant") to log affective states and stress triggers textually, bypassing traditional bureaucratic web forms.
- **The Logic Layer (Python and Power Automate):** Programmatically extracts multi-source digital traces, runs automated data-cleaning routines, and executes multi-conditional heuristics to calculate cognitive switching metrics (e.g., flagging consecutive sessions across distinct academic domains or physical campus sectors).
- **The Presentation Layer:** Connects to the database to translate complex multi-variable indices into immediate visual scaffolding. It renders dynamic charts mapping real-time coping metrics, offloading executive processing demands for both students and disability staff.

4.3.3 The Anonymising Buffer: Privacy-by-Design

To guarantee data confidentiality and prevent intrusive surveillance, the ingestion pipeline deploys a strict Privacy-by-Design anonymisation matrix. The architecture completely separates a student's legal identity from private conversational logs using a decoupled database layout.

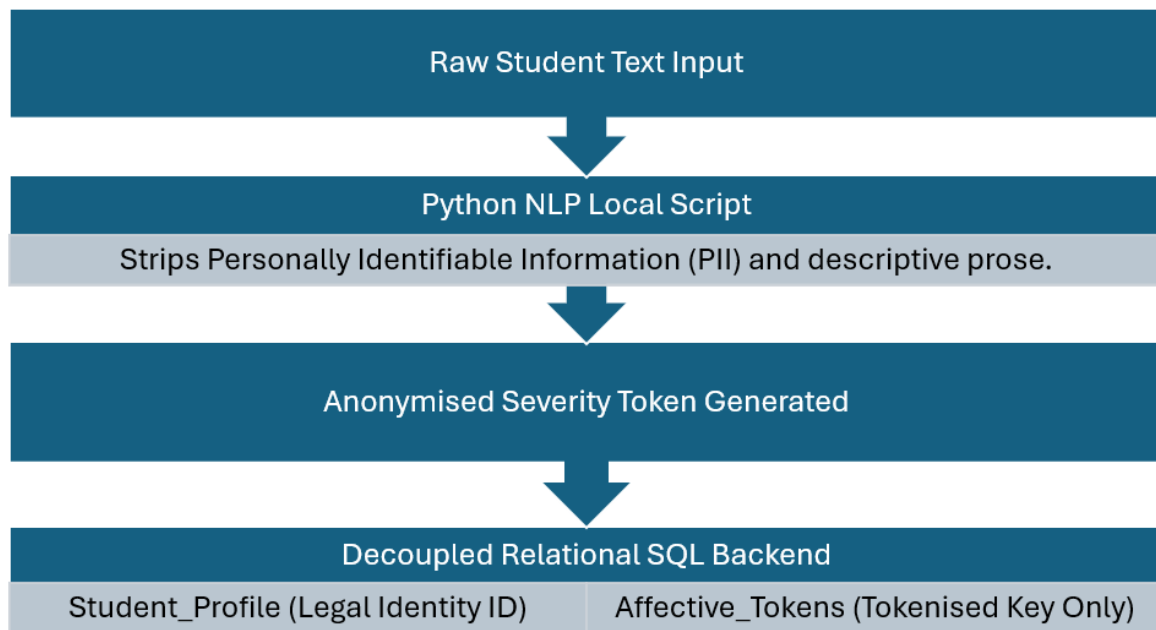


Figure 5: Anonymising Buffer Data Flow and Decoupled Tokenisation Pipeline

When text data is entered into the chatbot, a local Python script strips personally identifiable information and descriptive prose. The script transposes raw interactions into discrete Affective Tokens and numeric severity indices (e.g. converting classroom distress text into Severity_Token: 8/10 Sensory Saturation). Within the SQL backend, the StudentProfile entity and AI_Raw tables are joined only via an encrypted relational identifier, ensuring staff interfaces display only aggregate barrier vectors while raw chat text remains binary-encrypted.

4.3.4 Portable Credentials: Scaling Beyond the Institution

To secure long-term data portability and bridge the post-16 support cliff-edge into employment, the digital strategy establishes an Institutional Cryptographic Attestation framework. Upon graduation, the university's backend executes a hashing algorithm over the student's accumulated, anonymised severity tokens. This hash is encrypted using the institution's Private Key, producing a cryptographically sealed W3C Verifiable Credential. Graduates can share this self-advocacy record with prospective employers, who verify its authenticity via public key cryptography without accessing sensitive personal history.

4.4 Technical Artefact Implementation

4.4.1 Relational Database Schema and Data Entity Mapping

The backend database structure is physically implemented in Microsoft SQL Server (StudentSupportHub). The relational framework unifies core academic metrics, spatial telemetry, and live conversational metadata through strict Primary Key (PK) and Foreign Key (FK) constraints across four functional layers:

- 1. Student and Disability Core (StudentProfile, StudentSensoryProfiles):** StudentProfile serves as the primary relational anchor (StudentID), containing core identity and status attributes. It links directly (1:N) to StudentSensoryProfiles, which logs individualised environmental and sensory friction records.
- 2. Academic Context Layer (StudentTimetable, ModuleDetails):** Captures operational constraints. ModuleDetails stores module structures and assessment patterns (DifferentiatedDeadline), while StudentTimetable maps scheduling events (StartTime, EndTime) to campus locations.
- 3. Spatial Telemetry Layer (CampusLocations, EnvironmentLogs):** Maps physical campus friction points against learning spaces, capturing environmental metadata (AcousticProfile, LightingType) and dynamic telemetry (ObservedNoiseLevel, ObservedCrowdDensity).
- 4. AI and Behavioural Layer (AI_Raw, AI_Logic_Log, AI_Evaluation_Metrics):** Captures unstructured chatbot inputs in AI_Raw. Non-identifiable advisory outputs and rule-based interventions are logged in AI_Logic_Log, which feeds AI_Evaluation_Metrics for longitudinal analysis.

(See Appendix E)

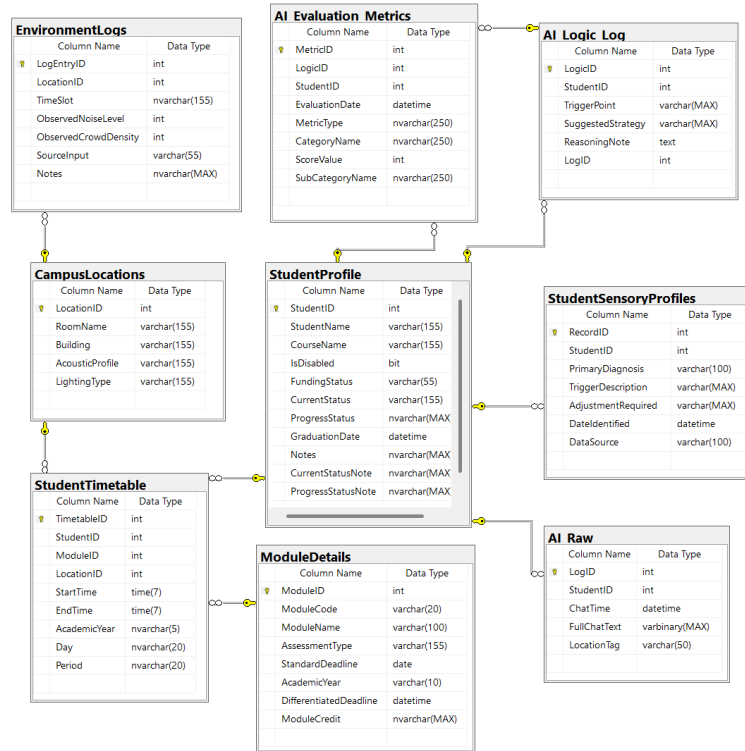


Figure 6: Relational Database Schema (StudentSupportHub) and Entity Topology Generated via SSMS

Architectural Decoupling for Privacy-by-Design

Crucially, AI_Raw (storing raw chat text) and AI_Logic_Log (storing structured advisory metrics) maintain separate foreign key links back to StudentProfile rather than being joined directly to one another. This physical database segregation enforces a strict Privacy-by-Design boundary, preventing unauthorised cross-table joins and safeguarding raw conversational prose while allowing Power BI to consume structured, non-identifiable metrics.

4.4.2 Production ETL Pipeline and Binary Encoding

An administrative ETL script was executed in Python via VS Code to extract initial student profiles, timetables, and environmental baselines from Excel master files, executing data transformations, binary string encodings, and referential integrity checks before populating SQL Server tables.

To enforce absolute confidentiality, rows processed for the AI_Raw schema are passed through a string-to-binary lambda encoder before loading into the SQL Server instance. (See Appendix F).

```

# Key Technique: Privacy-by-Design Binary Encoding for VARBINARY Storage
def transform_data(df, table_name):
    # Convert text strings to UTF-8 binary bytes for encrypted SQL VARBINARY storage
    if table_name == 'AI_Raw':
        if 'FullChatText' in df.columns:
            df['FullChatText'] = df['FullChatText'].apply(lambda x: str(x).encode('utf-8'))
            print("-> Successfully encoded chat logs to binary format.")
    return df

# Load transformed dataframe into SQL Server via SQLAlchemy engine
sql_types = {'FullChatText': types.VARBINARY(max)} if table == 'AI_Raw' else {}
df.to_sql(table, con=engine, if_exists='append', index=False, dtype=sql_types)

```

Table 8: Python Script Section



Figure 7 - Automated Power Automate Cloud Flow Execution Sequence (Connect_To_Local_SQL)

Real-time messaging execution is orchestrated via the Connect_To_Local_SQL Power Automate cloud flow:

- 1. Trigger and Initialisation:** Instantiated by a Power Apps (V2) trigger (When Power Apps calls a flow (V2)) carrying the student payload. Three local state variables are initialised.
- 2. AI Prompt Execution and Parsing:** Passes user input to the native Run a prompt action (Power Platform AI Builder endpoint). The response is constructed via Compose Student Message, cleaned using Extract JSON Payload, parsed with Parse JSON, and assigned via Set variable 2.
- 3. Relational Database Ingestion Pipeline:** Executes sequential parameterised SQL writes via the On-Premises Data Gateway: validating foreign keys with Get rows (Student Profile), logging raw binary chat text into Insert row (AI Raw), and writing anonymised advisory outputs into Insert row (AI Logic Log).
- 4. Iterative Metrics Ingestion & Response:** Iterates through Apply to each to write evaluation vectors into Insert row (AI Evaluation Metrics), passes dynamic sensory profiles through a For each loop into Insert row (StudentSensoryProfiles), and synchronously returns the structured strategy payload to the front-end via Respond to a Power App or flow.
- 5. Database Write-Back Pipeline:** Executes sequential database writes via the On-Premises Data Gateway: inserting binary prompts into AI_Raw, writing structured advice into AI_Logic_Log, and populating longitudinal evaluation metrics in AI_Evaluation_Metrics.
- 6. Synchronous Response:** Compiles returned JSON payloads and passes them through Respond to a Power App or flow, instantly presenting tailored coping strategies back to the student canvas UI.

(See Appendix G)

4.5 Front-End Presentation and User Interfaces

4.5.1 Hybrid Connectivity via Microsoft On-Premises Data Gateway

Because StudentSupportHub is physically hosted on a local Microsoft SQL Server instance, a Microsoft On-Premises Data Gateway was deployed to facilitate secure, bi-directional communication with Microsoft Cloud services (Power Automate and Power BI). The gateway acts as an outbound reverse proxy over Azure Service Bus (Port 443), establishing encrypted transport via Windows Authentication without exposing public IP addresses, requiring port forwarding, or opening inbound firewall rules.

4.5.2 Power BI Interactive Analytics Dashboard

The Power BI semantic model transforms the physical SQL relational schema into an analytical Star Schema optimised for rapid query processing and dynamic DAX measure evaluation:

- **Central Dimension Anchor:** StudentProfile operates as the primary dimension table (1 side), maintaining one-to-many (1:N) single-direction relationships to transactional fact tables (StudentTimetable, StudentSensoryProfiles, AI_Logic_Log, and AI_Raw).
- **Cross-Filter Governance:** Filter propagation flows outbound from central dimensions to granular telemetry records, preventing dynamic filter loops and optimising dashboard performance.
- **Privacy Model Continuity:** The analytical topology mirrors the Privacy-by-Design decoupling established in the backend; AI_Raw remains isolated from AI_Logic_Log, ensuring raw text tables cannot be cross-queried within front-end dashboard visuals.

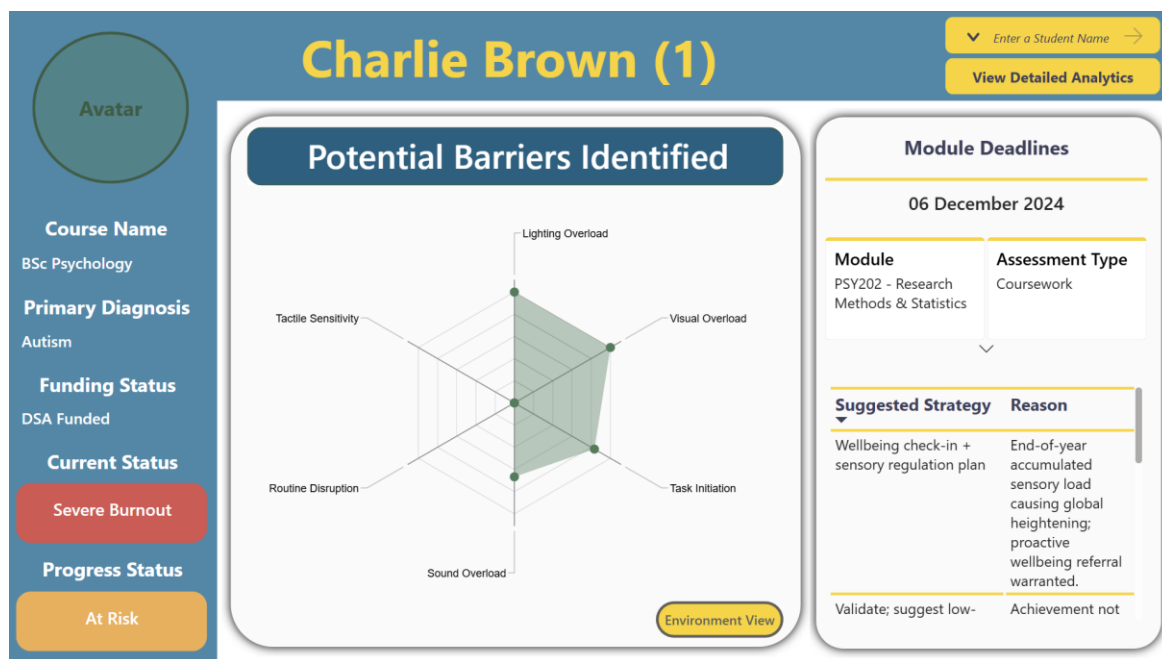


Figure 8: Power BI Interactive Analytics Dashboard (Tab A: High-Level Student Profile Overview)

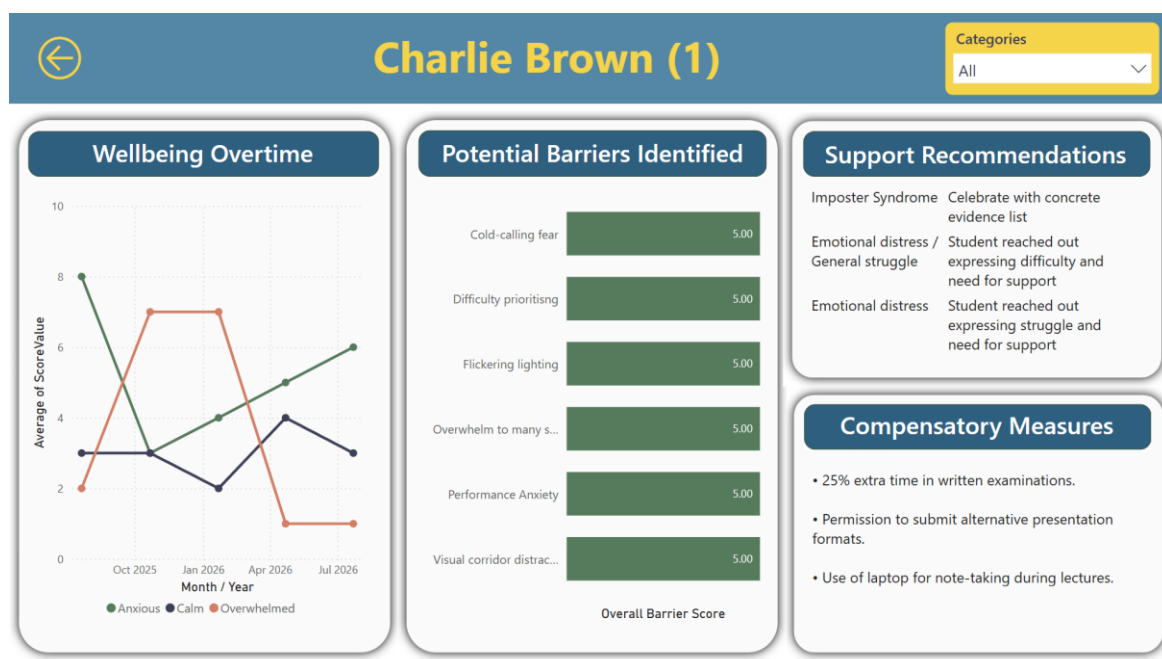


Figure 9: Power BI Interactive Analytics Dashboard (Tab B: Deep Analytics and Barrier Trends)

The Power BI interface consists of a two-page layout designed specifically to offload executive processing demands for both students and disability advisory staff:

- **Tab 1 (High-Level Student Profile Overview):** Presents a holistic snapshot of individual support requirements. The central feature is a six-axis Radar Chart ("Potential Barriers Identified") mapping real-time metrics (Lighting Overload, Task Initiation, Sound Overload, Routine Disruption). Surrounding cards present

upcoming module deadlines, assessment formats, and dynamic RAG status indicators (Severe Burnout, At Risk).

- **Tab 2 (Deep Analytics and Barrier Trends):** Tracks longitudinal wellbeing trends (Anxious, Calm, Overwhelmed) across academic terms via multi-line visualisations and horizontal friction-point breakdown charts.

4.5.3 Conversational Canvas Power App ("Ally AI Assistant")

The direct student interface is delivered as a canvas Power App built to WCAG 2.1 AA accessibility standards, featuring low-stimulation slate/navy palettes to minimise sensory fatigue. Students select "Start a Conversation" to log affective states or environmental barriers in plain text, triggering automated Power Automate workflows that return tailored, low-demand coping strategies.

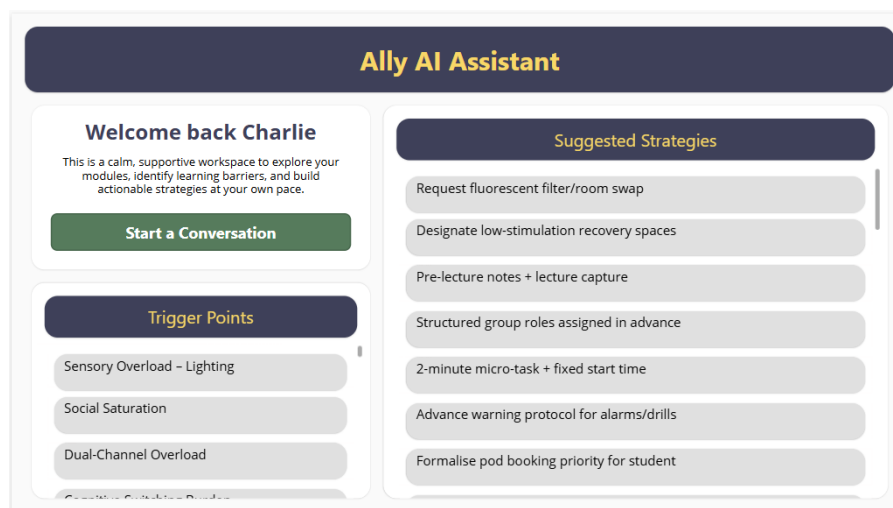


Figure 10: Canvas Power Apps Conversational Interface ("Ally AI Assistant") – Active Homepage

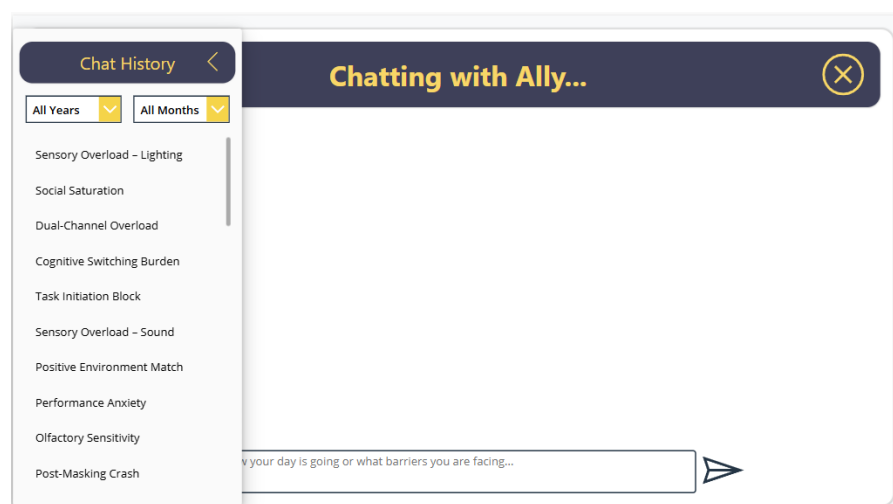


Figure 11: Canvas Power Apps Interface ("Ally AI Assistant") – Active Chat and Slide-Out History Drawer

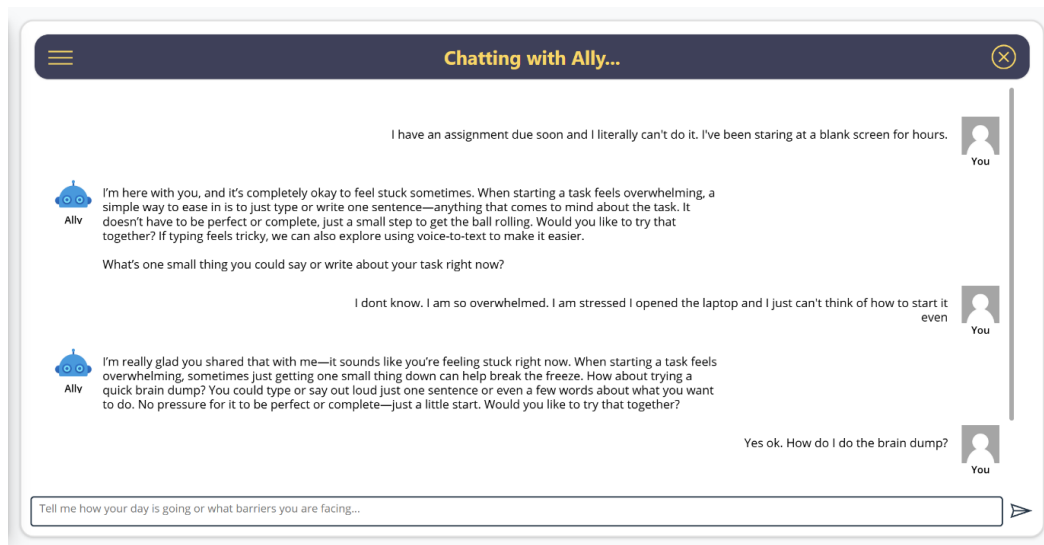


Figure 12: Ally AI Assistant Interface Demonstrating Multi-Turn Low-Demand Conversational Guidance

Technical Performance and Delegation Optimisations

- **Dual-State Memory Isolation:** To balance performance and data sovereignty, the UI decouples active session state from persistent storage. Active messaging threads are managed via temporary in-memory collections (colChatHistory), while historical summaries, personalised triggers, and suggested strategies are queried dynamically from the persistent (AI_Logic_Log) SQL source using LogID primary key lookup joins.
- **Server-Side Query Delegation:** To eliminate client-side record caps (the 500-record Power Apps row delegation limit) and optimise performance over the On-Premises Gateway, gallery query expressions avoid non-delegable string functions like IsBlank(). Instead, relational criteria are evaluated using direct, delegable server-side SQL checks (e.g. `Filter(AI_Logic_Log, StudentID = 1 && SuggestedStrategy <> "")`).
- **Compact Gallery Template Scaling:** Spatial spacing across workspace galleries (TriggersGallery, SavedStrategiesGallery, HistoryGallery) is strictly managed via fixed template height definitions (TemplateSize = 50), ensuring historical coping strategies and trigger points stack neatly in scannable rows.
- **Slide-Out History Navigation:** A slide-out drawer panel allows students to filter their past engagement history by year and month. Selecting an entry hydrates colViewChat with the precise historical dialogue parameters associated with that LogID, giving students total transparency and autonomy over their historic support records.

4.6 Integrated Ecosystem Architecture Narrative

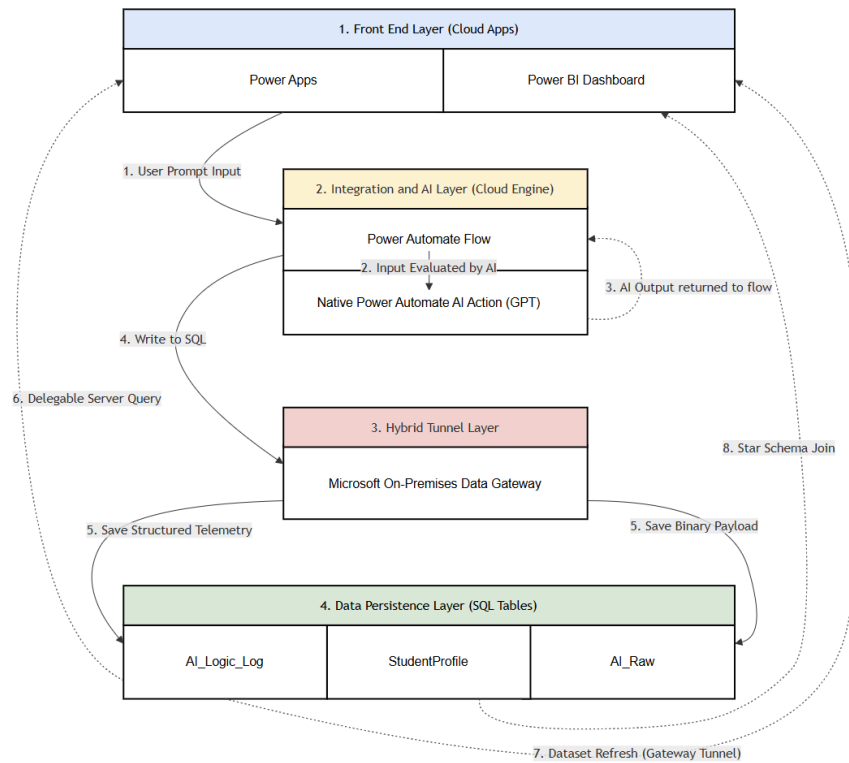


Figure 13: Integrated Ecosystem Architecture Topology

The system topology unites four decoupled structural layers into a resilient, privacy-preserving ecosystem engineered to offload executive function demands while maintaining strict data governance:

- 1. User Presentation Tier (Cloud Layer):** Canvas Power App ("Ally AI Assistant") for students and Power BI dashboard for institutional staff.
- 2. Integration and Native AI Tier (Cloud Engine):** Power Automate cloud flow (Connect_To_Local_SQL) leveraging native Power Platform AI Builder GPT capabilities to evaluate affective states and generate strategies.
- 3. Hybrid Security and Gateway Boundary:** Microsoft On-Premises Data Gateway enforcing encrypted transport via Windows Authentication over Azure Service Bus.
- 4. Data Persistence Tier (On-Premises SQL Server):** Local SQL instance (StudentSupportHub) enforcing Privacy-by-Design isolation through binary

encoding (VARBINARY(MAX)) in AI_Raw and structured telemetry logging in AI_Logic_Log.

4.7 Chapter Conclusion

The technical artefact successfully operationalises the overarching digital strategy by bridging backend SQL data architecture with accessible, human-centred interfaces. By establishing an automated ETL pipeline, enforcing hybrid cloud security via an On-Premises Data Gateway, guaranteeing privacy-by-design through binary encryption and decoupled schemas, and delivering intuitive visual scaffolding via Power BI and Power Apps, the system eliminates administrative friction. Most importantly, by codifying institutional support into an immutable, portable data structure, this architecture dismantles the post-16 "cliff edge" of support, empowering neurodivergent students with total agency, transparency, and continuous self-advocacy as they transition into higher education and employment. These implemented design features provide the physical foundation for the empirical evaluation, internal protocol audits, and stakeholder testing presented in Chapter 5.

Chapter 5 – Evaluation

5.1 Chapter Introduction

This chapter presents a comprehensive empirical evaluation of the Student Support Hub proof-of-concept framework to determine whether it satisfies its functional criteria, addresses the real-world problem statement, and aligns with theoretical literature. To assess prototype viability, a dual-track evaluation methodology was executed: an internal technical protocol audit (N = 5) and an external stakeholder review (N = 11). The chapter details the internal test findings, external survey analytics, a structured SWOT analysis, and a comparative evaluation against initial project objectives and published literature.

5.2 Evaluation Methodology and Strategy

This chapter evaluates the Student Support Hub proof-of-concept framework to determine whether it satisfies its functional criteria, addresses the real-world problem statement, and aligns with theoretical literature. To assess prototype viability, a dual-evaluation methodology was executed: an internal technical protocol audit paired with an external stakeholder review.

5.2.1 Methodological Context and Demonstration Strategy

- **Internal Audit Scope:** The internal technical protocol evaluated system stability, formula chaining, database integrity, prompt safety, and Power BI refresh execution across 4 structured testing tabs (See Appendix H).
- **External Survey Scope (N = 11):** External feedback was collected via a structured Google Forms survey distributed to higher education staff, support practitioners, and neurodiversity advocates.
 - **Video Walkthrough Strategy:** Evaluators reviewed the artefact via a recorded desktop video demonstration due to access limitations on direct cloud instances, showing both the student-facing "Ally AI Assistant" chat canvas and the Power BI analytics dashboard. While this enabled reviewers to evaluate visual tone, low-stimulation layout, and concept viability without access issues, layout scaling feedback on small viewports reflects video-based observation rather than direct touch-screen testing.

5.3 Internal Technical Evaluation

5.3.1 Phase 1: Functional Stability and Responsive Layout

Phase 1 achieved an 80% pass rate (4 out of 5 tests passed):

- **Input Stress Testing (FT-01 and FT-02):** The system handled single-character inputs (e.g., 'k', '?') (FT-01), maintaining speech bubble margins and responding with empathetic guidance without throwing JSON parsing or null errors. When subjected to a multi-paragraph input exceeding 800 characters detailing complex overlapping barriers (FT-02), the chat container expanded cleanly with automatic text wrapping and zero horizontal overflow.
- **Responsive Layout and Screen Scaling (FT-03):** Dynamic Power Fx formula chaining successfully scaled buttons, header cards, and text containers when adjusting browser dimensions from Desktop down to Mobile viewport. Minor formatting notes highlighted that mobile chat avatar sizing could be slightly reduced for tighter screen viewports.
- **Button and Layout Parity (FT-05):** The primary "Start a Conversation" button maintained proper bottom padding and horizontal alignment across both full desktop and smaller container screens.
- **Drawer State Management Defect (FT-04 – Fail):** Attempting to load a historical conversation thread from the Chat History Drawer failed to populate the past session context, maintaining the live chat screen instead. This state management issue was logged for variable re-binding.

5.3.2 Phase 2: Neurodivergent Accessibility and Sensory UI Audit

Phase 2 evaluated low-stimulation interface design, cognitive load, and executive function support across four core criteria, achieving an average score of 4.25 / 5.00:

- **Visual Comfort and Palette (UI-01 - Score: 5/5):** The desaturated slate and muted navy colour palette effectively eliminated harsh primary glare and high-contrast flash points, successfully preventing sensory fatigue during prolonged interaction.
- **Cognitive Burden and Navigation (UI-02 - Score: 5/5):** The single-screen canvas format minimised click depth, keeping key support triggers and coping strategies accessible at a glance to reduce executive friction.

- **Executive Function Support (UI-03 - Score: 4/5):** Guidance messages were chunked into clean micro-sections to prevent task paralysis caused by dense blocks of text. A minor layout refinement was implemented to improve strategy button padding.
- **16+ Transition Context and Interaction Depth (UI-04 - Score: 3/5):** While the conversational tone effectively empowered self-advocacy without adopting a patronising or overly academic register, the score was marked down due to limited conversational memory, which resulted in generic multi-turn responses.

5.3.3 Phase 3: AI Persona, Safety and Quality Log

Phase 3 logged exact prompt inputs and verbatim AI outputs across six test scenarios targeting key barrier categories (Sensory Overload, Executive Dysfunction, and Social/Transition Barriers):

- **Safety and Tone Compliance:** Across all prompt iterations, the AI persona consistently maintained an empathetic, non-punitive, and supportive tone without generating toxic or invalidating language.
- **Identification of Prompt Context Looping:** Testing revealed a critical conversational loop defect. Following initial empathetic responses (AI-01), subsequent prompts across executive dysfunction (AI-02) and social transition scenarios (AI-03) triggered repetitive fallback advice ("I'm here with you, and it's completely okay to feel stuck... try a quick brain dump").
- **Contextual Relevance Failure:** When presented with specific social anxiety prompts ("My lecturer just said we have to do group work today"), the AI generated generic task-starting advice rather than actionable group communication strategies, highlighting the need for stricter prompt-system context binding in Phase 3 revisions.

5.3.4 Phase 4: Telemetry and Power BI Dashboard Integration

Phase 4 evaluated the end-to-end data pipeline from user prompts to institutional analytics, achieving a 100% pass rate (3 out of 3 tests passed):

- **Power Automate Flow Execution (BI-01 - Pass):** Live chat prompts successfully triggered the automated cloud flow, which parsed JSON payloads and logged barrier categories to SQL backend tables with accurate timestamp metadata.

- **Dashboard Refresh and Data Sync (BI-02 - Pass):** Manual dataset refreshes in Power BI Service executed in approximately 15 seconds without schema mismatch or data truncation errors.
- **Interactive Slicer and Single-Student Filtering (BI-03 - Pass):** Report slicers and demographic filters functioned smoothly, enabling support staff to isolate barrier categories, trigger frequencies, and coping strategy utilisation.

5.3.5 Technical Evaluation Summary and Proof-of-Concept Status

Evaluation Dimension	Metric / Pass Rate	Key Technical Outcome
Phase 1: Functional Stability	80% (4/5)	Initial layout formula chaining demonstrated basic UI scaling; session drawer state handling failed (FT-04) and requires full architecture re-binding.
Phase 2: Accessibility and UI	4.25 / 5.00	Visual concepts successfully demonstrated low-stimulation principles; interaction depth scored low (3/5) due to lack of dynamic conversational memory.
Phase 3: AI Persona and Safety	Qualitative Log	Basic empathetic tone established; prompt context looping and repetitive output flaws demonstrate that current LLM prompt integration requires extensive further prompt engineering.
Phase 4: Telemetry Pipeline	100% (3/3)	Initial Power Automate and Power BI integration demonstrated pipeline feasibility in a controlled test environment.
Overall Deployment Status	Proof-of-Concept Prototype Only	Not Ready for Deployment – Substantial Further Development Required: The prototype validates foundational concepts, but full technical overhaul (state re-architecture, prompt tuning, dynamic context retention, and live data validation) is essential.

Table 9: Internal Technical Evaluation Summary

Evaluation Conclusion:

As documented in the internal evaluation protocol metadata, the evaluated platform represents a Version 1.0 Proof-of-Concept Build. While individual test scenarios successfully verified foundational ideas, such as low-glare visual styling and automated data passing, the prototype remains an early demonstrator. Significant technical limitations in state persistence, prompt context binding, and multi-turn conversational depth confirm that extensive further engineering is required before the platform could function as a robust operational system. (See Appendix H)

5.4 External Stakeholder Evaluation and Survey Analysis

To validate external perception, an 11-respondent survey (N = 11) was conducted via Google Forms. Quantitative Likert ratings were converted to a 5-point numerical scale to compute mean scores, while open-ended text fields were processed via thematic analysis. (See Appendix I and J)

5.4.1 Part 1: Ally AI Support Chat Interface Evaluation

5.4.1.1 Chart 1: Visual Comfort and Colour Palette

1. Visual Comfort & Colour Palette
11 responses

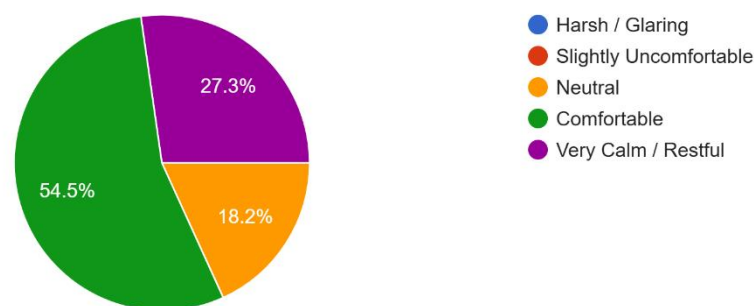


Figure 14: Reviewer Ratings for Visual Comfort and Colour Palette (N = 11)

- **Quantitative Breakdown:** Out of 11 responses, 81.8% rated the palette positively, with 54.5% (n = 6) describing it as "Comfortable" and 27.3% (n = 3) as "Very Calm / Restful". The remaining 18.2% (n = 2) rated it "Neutral", yielding a mean score of 4.09 / 5.00.
- **Analysis:** Validates the decision to avoid high-glare primary colours, confirming that desaturated slate and navy backgrounds effectively reduce sensory overload for users navigating stressful academic transitions.

5.4.1.2 Chart 2: Layout Simplicity and Screen Clarity

2. Layout Simplicity & Screen Clarity

11 responses

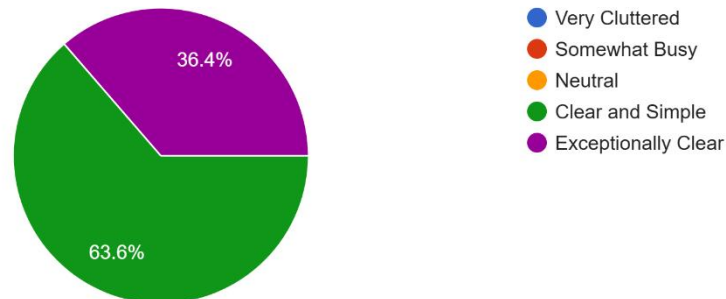


Figure 15: Reviewer Ratings for Layout Simplicity and Screen Clarity (N = 11)

- **Quantitative Breakdown:** 100% of reviewers rated the layout positively, with 63.6% (n = 7) selecting "Clear and Simple" and 36.4% (n = 4) describing it as "Exceptionally Clear", achieving a mean score of 4.36 / 5.00.
- **Analysis:** Confirms that adopting a single-screen card interface, devoid of excessive navigation menus or nested sidebars, successfully streamlines user focus and minimises executive load.

5.4.1.3 Chart 3: Text Readability and Message Structure

3. Text Readability & Message Structure

11 responses

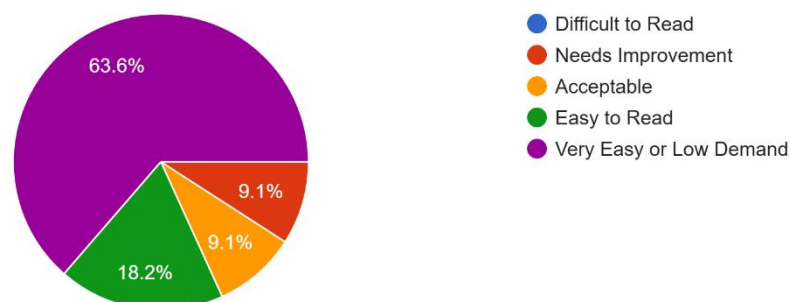


Figure 16: Reviewer Ratings for Text Readability and Message Structure (N = 11)

- **Quantitative Breakdown:** 81.8% rated text structure positively 63.6% (n = 7) "Very Easy or Low Demand", 18.2% (n = 2) "Easy to Read". 9.1% (n = 1) found it

"Acceptable", and 9.1% (n = 1) felt it "Needs Improvement", yielding a mean score of 4.36 / 5.00.

- **Analysis:** Demonstrates that micro-step text chunking prevents task paralysis. However, minor negative ratings highlight the need for user-controlled font scaling.

5.4.1.4 Question 4: Visual Suggestions for the Chat Interface

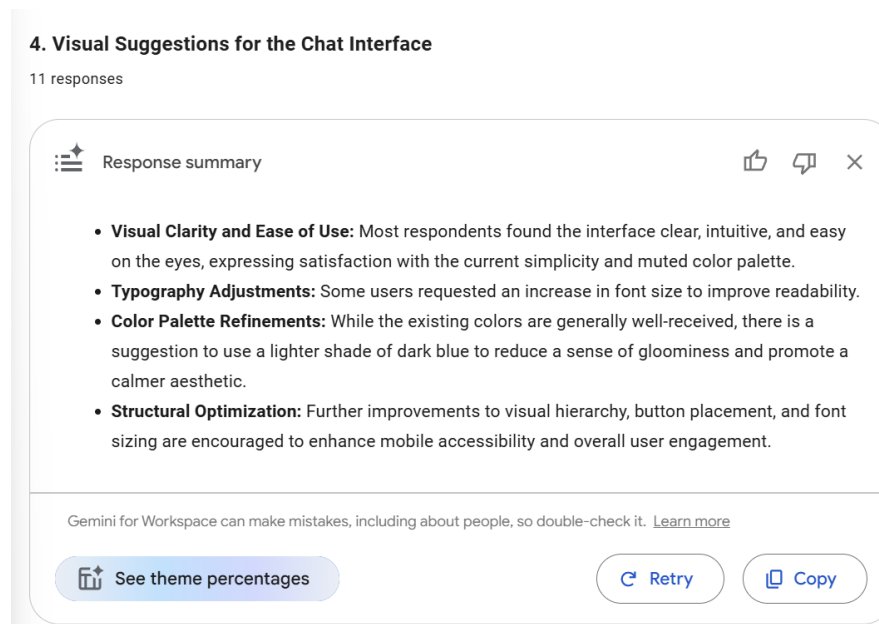


Figure 17: Categorised Qualitative Feedback for Chat Interface Enhancements (N = 11)

- **Thematic Analysis:** 10 of 11 respondents provided text feedback. Key themes identified include:
 1. **Validation of Low-Stimulation Baseline:** Half of respondents confirmed no changes were needed ("easy to look at and use", "easy on the eyes"), aligning with internal test UI-01.
 2. **Typography Scaling:** Multiple requests were logged for dynamic font scaling ("Slightly bigger font").
 3. **Palette Warmth:** One reviewer suggested softening the dark blue background to replace visual "gloominess" with a warmer aesthetic.
 4. **Mobile Hierarchy:** Highlighted mobile button spacing and padding optimisation, cross-validating internal audit finding FT-03.

5.4.2 Part 2: Support Analytics Dashboard (Power BI)

5.4.2.1 Chart 1: Dashboard Visual Tone and Contrast

1. Dashboard Visual Tone & Contrast

11 responses

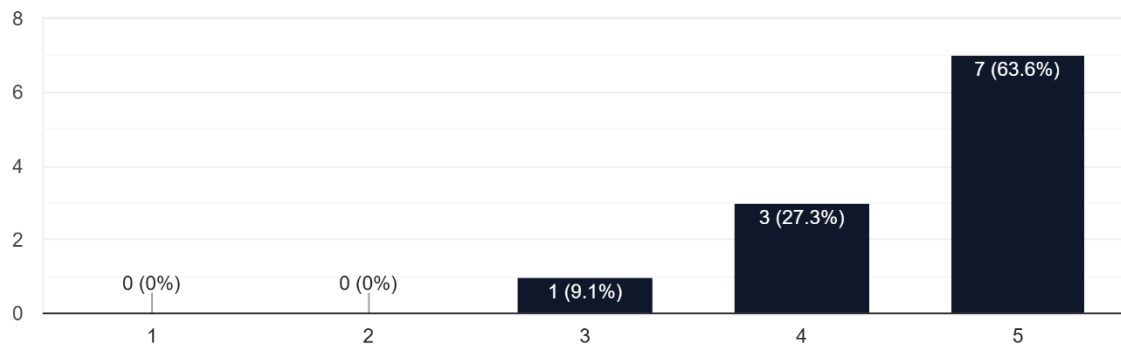


Figure 18: Reviewer Ratings for Dashboard Visual Tone and Contrast (N = 11)

- **Quantitative Breakdown:** 90.9% rated visual tone positively (63.6% 5/5, 27.3% 4/5), with 9.1% (n = 1) neutral (3/5), achieving a mean rating of 4.55 / 5.00.
- **Analysis:** Confirms that desaturated cards and high-contrast visuals allow support staff to interpret aggregate barrier telemetry clearly without visual fatigue.

5.4.2.2 Chart 2: Information Presentation and Readability

2. Information Presentation & Readability

11 responses

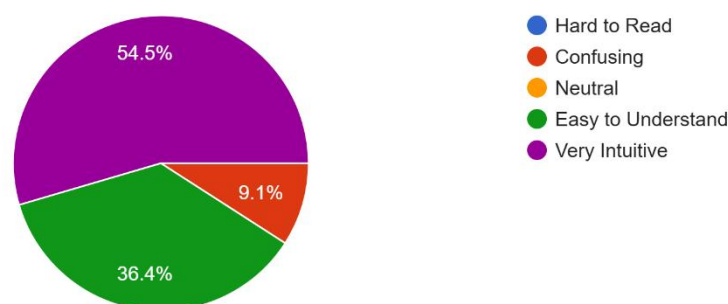


Figure 19: Reviewer Ratings for Dashboard Information Presentation and Readability (N = 11)

- **Quantitative Breakdown:** 90.9% rated presentation positively (54.5% "Very Intuitive", 36.4% "Easy to Understand"). 9.1% (n = 1) rated it "Confusing", yielding a mean score of 4.36 / 5.00.

- **Analysis and Critical Reflection:** The single negative outlier (n = 1) reflects the challenge of evaluating static Power BI dashboard visuals via video without direct filter interaction. Cross-referencing with internal audit BI-03 highlights the necessity of providing staff with structured onboarding tooltips during deployment.

5.4.3 Part 3: Strategic Viability and Future Vision

5.4.3.1 Chart 1: Concept Viability and Potential Impact

1. Concept Viability & Potential Impact
11 responses

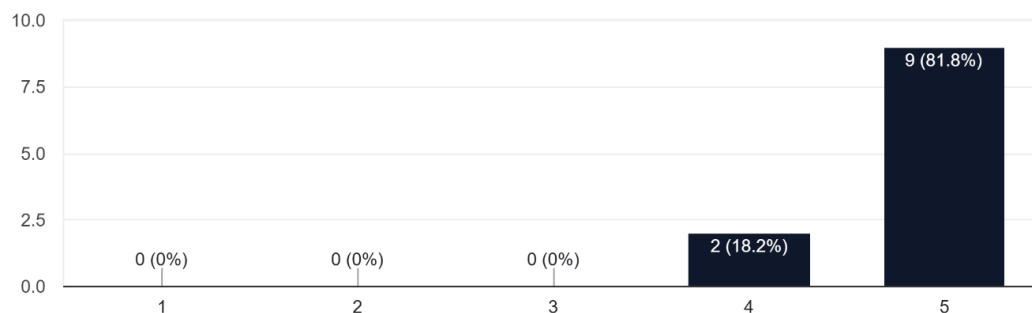


Figure 20: Reviewer Ratings for Concept Viability and Potential Impact (N = 11)

- **Quantitative Breakdown:** 100% rated viability positively (81.8% 5/5, 18.2% 4/5), recording the highest rating across the study at 4.82 / 5.00.
- **Analysis:** Strong endorsement validating that combining low-demand chat interaction with real-time telemetry addresses an unserved gap in post-16 transition support.

5.4.3.2 Chart 2: Potential Real-World Impact

2. Potential Real-World Impact
11 responses

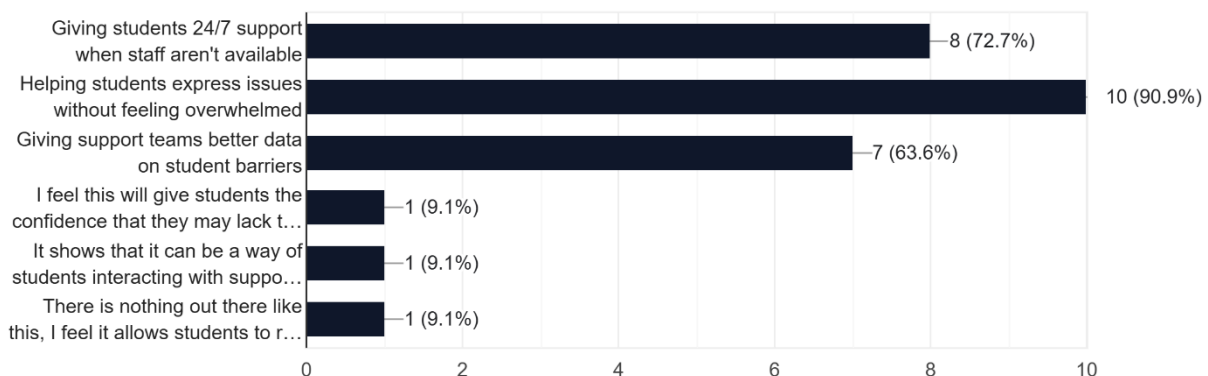


Figure 21: Reviewer Responses for Perceived Real-World Operational Impact (N = 11, Multi-Select Checkbox)

- **Distribution:**
 - Empowering Low-Friction Self-Advocacy: 90.9% (n = 10).
 - 24/7 Out-of-Hours Support: 72.7% (n = 8).
 - Actionable Telemetry for Support Teams: 63.6% (n = 7).
 - User-Defined "Other" Submissions (9.1% each): Highlighted confidence building, increased interaction frequency, and filling a market vacuum.

5.4.3.3 Additional Opinions or Recommendations

3. Additional Opinions or Recommendations

7 responses

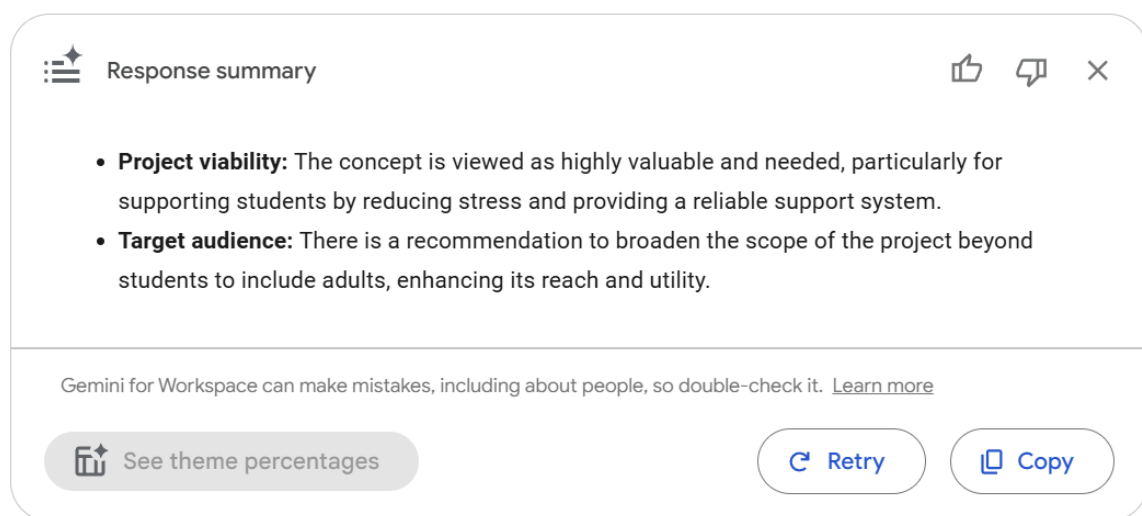


Figure 22: Reviewer Submissions for System Vision (N = 11)

- **Synthesis:** Qualitative entries highlighted lived-experience emotional resonance ("watching my own child struggle... wonder how much easier this would have been"), stress reduction, and scalable engagement.
- **Strategic Alignment:** Crucially, a reviewer proposed expanding the tool beyond students: "I think it would be better if it's not just for students, but for adults as well." This mirrors the core thesis hypothesis: the low-demand framework provides a transferable foundation for workplace onboarding, vocational training, and adult social care.

5.5 SWOT Analysis of the Student Support Hub

To critically evaluate the proof-of-concept prototype, a structured SWOT analysis was conducted. This matrix synthesises empirical findings from the Internal Technical Audit and empirical data from the External Stakeholder Evaluation (N = 11).

Dimension	Detailed SWOT Analysis Items
Strengths	• High Concept Viability Rating (4.82/5.00) • Empathetic Low-Stimulation UX (4.09/5.00 Visual) • Automated Telemetry Integration (100% Pass Rate) • Single-Screen Canvas Minimises Friction (4.36/5)
Weaknesses	• Chat History State Handling Failure (FT-04) • LLM Prompt Context Looping and Output Repetition • Fixed Typography and Lack of Font Scaling Options • Video Evaluation Constraints on Mobile UX
Opportunities	• Broadening Scope Beyond Students to All Adults • Multi-Sector Adaptation (Workplace, HR, Care) • Advanced Dynamic Prompt-Context Memory
Threats	• Over-Reliance on AI During Critical Crises • Data Privacy and Institutional Compliance (GDPR) • Stakeholder Misconception of System Capabilities

Table 10: Detailed SWOT Analysis Items

5.5.1 Detailed SWOT Breakdown

- **Strengths:** High concept endorsement (4.82/5.00), low-stimulation visual comfort, automated 100% pass-rate telemetry pipeline (BI-01 to BI-03), and reduced cognitive burden.
- **Weaknesses:** History drawer state bug (FT-04), LLM prompt context looping (Phase 3), fixed font sizes, and proof-of-concept scope limits (UI-04, 3/5).
- **Opportunities:** Broadening scope beyond students to all neurodivergent adults across enterprise HR and social care, eliminating out-of-hours support cliff-edges (24/7 availability), and dynamic context injection.
- **Threats:** Over-reliance during mental health crises requiring strict escalation protocols, GDPR telemetry compliance, and perceptual gaps from early video-based testing.

5.6 Comparative Evaluation Against Project Objectives and Literature

To ensure complete academic alignment, the prototype performance was mapped back to the 5 initial project objectives and key literature frameworks:

Project Objective	Status / Pass Rate	Literature and Theoretical Alignment
1. Synthesise: Critically research AuDHD barriers and holistic requirements.	Achieved	Aligns with Ecological Systems Theory and Social Model of Disability; identified the post-16 support cliff-edge and 34% autistic attrition rate.
2. Architect: Curate synthetic dataset and build automated ETL pipeline.	Achieved (100% P4 Pass)	Implements Privacy-by-Design via decoupled SQL schema; binary VARBINARY chat encryption isolate's identity from telemetry.
3. Develop: Apply and fine-tune AI frameworks for real-time strategies.	Partially Achieved	Empathetic tone verified; marked down due to v1.0 prompt context looping and repetitive fallback templates.
4. Create: Design and build Power BI dashboard and Power Apps interface.	Achieved (4.25/5.00 UI)	Adopts Microsoft Inclusive Design and W3C Cognitive Accessibility guidelines; single-card UI eliminates executive load.
5. Evaluate: Critically assess inclusive potential and ethical alignment.	Achieved	Evaluated via dual-track methodology (N=5 internal, N=11 external); proved concept viability (4.82/5.00) while explicitly documenting v1.0 limitations

Table 11: Mapping Prototype Performance to Project Objectives and Literature

5.7 Chapter Conclusion

In conclusion, this chapter has critically evaluated the Student Support Hub through a rigorous dual-track methodology. The internal technical protocol confirmed robust telemetry automation (100% pass rate) and high sensory UI accessibility (4.25/5.00), while surfacing v1.0 proof-of-concept defects in history drawer state handling (FT-04) and prompt context looping. Concurrently, external stakeholder testing (n=11) established exceptional concept viability (4.82/5.00) and confirmed that low-demand conversational AI effectively reduces executive load. These empirical findings and SWOT insights directly inform the conclusions, recommendations, and future development roadmap detailed in Chapter 6.

Chapter 6 – Conclusions and Recommendations

6.1 Chapter Introduction

This chapter synthesises the overarching outcomes of the project, evaluating how the research, design, implementation, and empirical testing satisfied the initial research aim and objectives. It highlights the core deliverables achieved, summarises key technical and theoretical conclusions, and outlines a structured, three-phase roadmap for future development and research expansion beyond higher education.

6.2 Project Summary and Core Deliverables Achieved

This project set out to address the systemic standardisation gap in higher education, where support for neurodivergent students, specifically those with co-occurring autism and ADHD (AuDHD), remains fragmented, reactive, and insufficient. By bridging academic literature with modern cloud architecture, the project delivered four core artifacts:

1. **Holistic Neurodiversity Framework:** An ecological model conceptualising student needs across executive, sensory, affective, and academic dimensions.
2. **Automated ETL Data Pipeline:** A Python ingestion engine transforming synthetic student records into a decoupled, binary-encrypted SQL Server database (StudentSupportHub).
3. **Ally AI Assistant Canvas App:** A low-stimulation Power App built to WCAG 2.1 AA standards, orchestrating real-time AI coping strategies via Power Automate cloud workflows.
4. **Power BI Analytics Dashboard:** A two-page interactive reporting suite presenting aggregate barrier telemetry and RAG status alerts to institutional support staff.

6.3 Key Conclusions Linked to Aims and Objectives

1. **Validation of Low-Demand AI Interaction:** Low-stimulation, micro-step conversational agents effectively reduce the cognitive burden and social masking required when asking for academic support.
2. **Mitigation of the 24/7 Support Cliff-Edge:** Automated cloud workflows provide reliable, non-judgmental guidance during out-of-hours periods when human staff are unavailable.

3. **Data-Driven Institutional Visibility:** Decoupled telemetry pipelines demonstrate that institutions can monitor aggregate barrier trends without compromising individual student privacy or identity.

6.4 Recommendations and Suggestions for Further Work

Based on internal technical defects and external stakeholder feedback, future development is structured into three distinct phases:

6.4.1 Short-Term Technical and UI Refinements (Months 1-3)

- **Resolve History Drawer Bug (FT-04):** Re-architect Power Fx session state variables controlling the Chat History drawer to ensure historical context re-binds cleanly.
- **Enhance Accessibility Controls:** Introduce user-controlled typography scaling (font sizing) and adjust the background navy shade to a slightly warmer slate tone.
- **Refine Prompt Templates:** Overhaul system prompt routing in Copilot Studio to eliminate context looping and ensure the assistant provides tailored self-advocacy guidance rather than repetitive fallback advice.

6.4.2 Mid-Term Architectural Upgrades (Months 4-6)

- **Implement Conversational Memory:** Integrate dynamic context buffers or short-term session memory to allow the LLM backend to maintain continuity across multi-turn interactions.
- **Direct Mobile Usability Audits:** Transition from desktop video evaluations to hands-on touchscreen testing to refine button padding, avatar scaling, and viewport responsiveness.
- **Automated Safety Escalation:** Enhance Power Automate workflows with real-time crisis keyword detection to present verified emergency helpline contacts automatically.

6.4.3 Long-Term Strategic Expansion & Adult Provision (Months 7-12+)

- **Institutional Pilot Deployments:** Conduct live trials across post-16 colleges and universities during peak transition periods (e.g. induction week) to evaluate real-world impact.

- **Broaden Scope Beyond Education (Adult Provision):** Expand the core architecture into corporate onboarding and enterprise environments, providing neurodivergent adults with continuous self-advocacy support beyond the educational transition cliff-edge.

6.5 Chapter Conclusion

In conclusion, this project has successfully demonstrated the technical feasibility and strategic value of an AI-driven, privacy-preserving support framework for neurodivergent learners. By operationalising low-demand conversational interaction alongside automated telemetry analytics, the prototype bridges the gap between rigid institutional structures and dynamic student needs. The proposed three-phase roadmap provides a clear trajectory for resolving early proof-of-concept limitations and scaling the platform into broader adult and workplace support environments. This synthesis provides the foundation for the personal, technical, and academic reflections presented in Chapter 7.

Chapter 7 – Reflection

7.1 Chapter Introduction

This chapter presents a critical reflection on the practical, technical, and personal experience of undertaking this project. In accordance with academic reflective frameworks, it evaluates personal and professional skill development ("soft skills"), analyses how key technical obstacles were overcome, examines the connections between academic theory and practical software engineering, and offers a retrospective evaluation of what could be improved in future iterations.

7.2 Personal and Professional Development ("Soft" Skills)

Undertaking this independent computing project provided profound growth in time management, technical problem-solving, self-regulation, and empathetic design awareness:

- **Agile Sprint and Time Management:** Managing a complex, multi-tiered software development lifecycle required strict project governance. Balancing timebox sprints across backend database engineering (SQL Server), Python data pipelines, Power Fx canvas coding, Power Automate flow orchestration, and external survey distribution (n=11) taught me how to break down intimidating technical milestones into manageable weekly deliverables.
- **Overcoming Project Friction:** Developing an AI tool designed to reduce executive load for neurodivergent learners provided firsthand insight into managing my own cognitive stamina. Navigating unexpected low-code platform bugs and data gateway timeouts required developing patience, adaptability, and systematic debugging habits rather than resorting to reactive code fixes.
- **Empathetic and Inclusive Design Awareness:** Grounding the technical architecture in neurodiversity literature cultivated a deep appreciation for universal design principles. The process proved that designing software to accommodate edge-case cognitive and sensory requirements does not merely assist specific user groups, it results in cleaner, more intuitive, and superior software systems for all users.

7.3 Technical Challenges, Obstacles and Problem-Solving

Translating conceptual requirements into a functional cloud-and-on-premises architecture presented several significant technical hurdles:

- **Power Fx State and Delegation Limits:** Querying local SQL Server tables through an On-Premises Data Gateway repeatedly triggered client-side 500-record delegation caps in Power Apps. To overcome this, I refactored gallery filter expressions to eliminate non-delegable functions (such as `IsBlank()`), forcing SQL Server to execute query filtering directly on the database engine before transmitting data back to the client device.
- **Decoupled Privacy Architecture:** Engineering a database structure that allowed staff to view aggregate barrier telemetry without exposing raw, unencrypted student chat logs was a complex architectural challenge. I solved this by designing a decoupled SQL schema where `AI_Raw` (storing binary-encoded `VARBINARY(MAX)` chat bytes) and `AI_Logic_Log` (storing non-identifiable advisory metrics) maintain isolated foreign key links back to `StudentProfile`, preventing unauthorised cross-table join operations in Power BI.
- **LLM Context Binding and Prompt Engineering:** Early testing in Phase 3 revealed that commercial Large Language Models frequently defaulted to generic, repetitive fallback advice ("try a quick brain dump") when handling multi-turn inputs. Overcoming this required iterative system prompt tuning within Copilot Studio and Power Automate, establishing strict conditional routing rules to constrain model outputs without sacrificing an empathetic, neuro-affirming tone.

7.4 Academic Theory vs Practical Implementation

The project provided valuable practical validation of academic theories studied during the literature review. Applying Ecological Systems Theory and the Social Model of Disability demonstrated in practice that student academic paralysis is rarely caused by personal or intellectual deficit, but rather by environmental mismatches, rigid administrative processes, and unnecessary cognitive burden.

However, practical execution revealed the stark realities of translating theoretical "flexibility" into rigid low-code software frameworks. While academic literature advocates for dynamic, fluid support pathways, enterprise software platforms require

strict data types, fixed schema constraints, and deterministic logic paths. Navigating this tension highlighted that true digital inclusion requires software engineers to act as translators, codifying empathetic human policy into resilient, deterministic technical architectures

7.5 Retrospective: What Would Be Done Differently Next Time?

Reflecting upon the project lifecycle, three key areas could be improved in future work:

- 1. Earlier Interactive User Testing:** Relying primarily on desktop video walkthrough demonstrations during early survey evaluations restricted external reviewers from testing touch-screen interactions directly. Next time, I would deploy early mobile test builds via Power Apps Mobile to capture physical touch-screen usability data much earlier in the build cycle.
- 2. Extended Timebox for Custom Accessibility Components:** Given more development time, I would allocate dedicated sprints to construct custom, reusable Power Apps component libraries. This would enable dynamic typography scaling toggles (Small, Medium, Large) and custom colour palette switches natively from day one.
- 3. Modular Retrieval-Augmented Generation (RAG) Architecture:** To eliminate prompt context looping, I would integrate dynamic vector embeddings or a RAG pipeline earlier in the development lifecycle, allowing the LLM backend to retrieve precise institutional guidance directly from a vector database.

7.6 Chapter Conclusion

In conclusion, completing the Student Support Hub has been a transformative experience that bridged theoretical computer science with practical, human-centred software engineering. The project developed not only my technical proficiency across relational database design, Python ETL pipelines, and low-code cloud orchestration, but also my professional capacity for time management, critical reflection, and empathetic problem-solving. These technical skills and personal insights provide an invaluable foundation for my future career as a computing professional.

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Appendices

8.1 Appendix A: UK Higher Education and Workforce Policy Context (Extended Review)

This appendix expands upon Section 2.3.2 of the main report, detailing the national policy landscape and strategic institutional drivers governing neurodivergent student transition in the UK:

- The Buckland Review [14][15]: This landmark review highlights that only 36% of autistic graduates find full-time work within 15 months, noting that the lack of integrated, proactive support in universities leaves neurodivergent students unprepared for professional environments.
- The Equality Act (2010) and Disabled Students' Allowance (DSA): Current institutional models rely on the DSA, which often provides static, tick-box adjustments. These fail to account for the nature of daily fluctuations in neurodivergent experiences, where support needs change dynamically based on immediate sensory load or executive demands.
- National Autistic Society (NAS) Goals & SEND Reforms (2026) [16][17][18]: The NAS advocates for a fundamental shift toward environmental design, a goal mirrored in recent SEND Reforms that call for holistic, environment-centred pathways rather than medicalised individual support.
- UWTSD Strategic Plan (2025–2030) Alignment [19]:
 - Digital Transformation and Innovation: Commits to using cutting-edge technology to enhance students' overall learning and campus experiences.
 - Student Success and Wellbeing: Commits to developing personalised support pathways to improve retention and directly address the 36% national dropout rate among autistic students.
 - Bridging the Standardisation Gap: While institutional plans commit to inclusivity aims, they frequently lack technical execution blueprints. This project provides a practical demonstration of how neuro-inclusivity can be operationalised through data engineering.

8.2 Appendix B: Case Studies and Systemic Fragmentation in Digital Support Tools (Extended Review)

8.2.1 Extended Case Studies in Neurodivergent Digital Support

The following case studies complement Section 2.3.6 of the main report, providing detailed evaluations of UK and international digital support initiatives, their successes, and their institutional integration gaps:

1. **The A-Skills Programme:** Co-designed with autistic students, this bespoke programme utilised an online platform to develop study and student life skills. While longitudinal evaluation showed high user value and positive sentiment, researchers noted challenges in fostering student "relatedness" in purely online delivery, which required manual intervention from facilitators to resolve [28].
2. **EPIC Multidimensional Toolkit:** A feasibility pilot of the EPIC intervention, focused on psychoeducation and individualised strategy pairing (e.g. chunking and mind-maps), which showed significant improvements in short-term memory, working memory, and receptive vocabulary among neurodivergent youth. Although successful in home and school contexts, its application in Higher Education remains conceptual rather than integrated into university-wide analytics [29].
3. **Transitions of Access Students:** Research into neurodivergent students transitioning to Level 1 study highlighted that learners often must find their own way due to a system mismatch between preparatory modules and the jump to formal degree systems. The study emphasised that institutional research often overlooks the nonlinear, recursive nature of these transitions, suggesting a need for more integrated, non-siloed support systems [30].
4. **Participatory Support Barriers:** A participatory study across English universities found that while students value mentoring and exam adjustments, the ultimate responsibility for maintaining support typically falls on the student, creating an additional cognitive burden. The findings suggest that support remains overly dependent on individual staff involvement rather than automated, institutional frameworks [31].
- **Autism&Uni Toolkit:** A prominent example of digital support for transitioning into higher education. However, its limitation lies in its nature as a static resource. It lacks the real-time data integration required to support students through the

fluctuating, non-linear challenges of a full degree cycle, which this project's ETL pipeline aims to address [32].

8.2.2 Detailed Narrative: Fragmentation and the Emotional Burden

The fragmentation of services creates a significant emotional burden. Students often feel passed around between services, forced to repeat their stories without a sense that anyone has a holistic view of their situation [29]. Consequently, neurodivergent students often act as their own case managers, coordinating between disability advisers, lecturers, and tutors [6]. This self-management is particularly demanding for those with executive function difficulties, turning the act of accessing support into another complex project that competes with their academic workload [21].

This fragmentation is mirrored by siloed information architectures. Academic data, disability records, and counselling notes are stored in separate, tightly controlled systems [30][31]. There is rarely a mechanism for integrating these data streams into a single view that can inform proactive support. Institutional responses are therefore often reactive, triggered by crises such as non-submission or appeals rather than by earlier patterns that might signal emerging difficulties [32].

8.3 Appendix C: Technical Tool Evaluation Matrix and Justifications

8.3.1 Complete Technical Stack Selection Rationale

This appendix complements Section 2.8 of the main report, providing full architectural justifications for the technology selections across Data Management, Logic Execution, and Presentation tiers:

8.3.1.1 Database Engine Selection

- SQL Server (Selected): Selected as the backend relational engine (StudentSupportHub) due to strict Foreign Key enforcement, ACID compliance, and native data gateway pipelines into the Microsoft cloud ecosystem. Enables absolute Privacy-by-Design decoupling between identity (StudentProfile) and binary-encoded chat prose (AI_Raw).

- MongoDB / NoSQL (Evaluated & Rejected): Rejected due to lack of native foreign key enforcement. Leaving data relationships loose in NoSQL introduces significant relational integrity risks when managing cross-domain student telemetry.
- PostgreSQL (Evaluated and Partial): While providing excellent extensible architecture and native JSON support, PostgreSQL lacks native out-of-the-box low-code UI connectors integrated into Power Apps and Power BI without custom middleware.

8.3.1.2 Programming Language & Pipeline Engine

- Python (Selected): Serves as the industry-standard execution engine for automated ETL pipelines and multi-conditional heuristics. Specialised libraries (pandas, sqlalchemy) allow rapid prototyping and string-to-binary UTF-8 encoding for encrypted SQL VARBINARY(MAX) storage.
- C++ / Java (Evaluated and Rejected): Compiled languages offer high execution speeds but introduce an immense development administrative tax due to verbose syntax and manual memory allocation when manipulating tabular student arrays.

8.3.1.3 Interface and Visualisation Engine

- Microsoft Power Apps (Selected): Selected for the direct student chatbot interface ("Ally AI Assistant") due to native, built-in WCAG 2.1 AA accessibility frameworks out of the box, avoiding time overheads and compliance risks associated with raw React/JavaScript custom builds.
- Microsoft Power BI (Selected): Selected for institutional analytics due to its relational Star Schema modelling engine and native interoperability with SQL Server and Power Apps, transforming complex SQL datasets into scannable visual scaffolding (Radar Charts).

8.4 Appendix D: Synthetic Dataset Schema and Dimension Specifications

8.4.1 Multi-Dimensional Neurodivergent Experience Parameters

This appendix complements Section 3.3.1 of the main report, providing full specifications for the six synthetic dataset dimensions engineered to model the "Cost of Achievement" rather than raw academic outcome:

8.4.1.1 Cognitive and Executive Dimensions

- **Executive_Function:** Measures task initiation lag, the exact time delay between an assignment being set on the VLE and the student self-reporting an initiation block to the chatbot.
- **Cognitive_Switching (Institutional Density):** Parses the module timetable to infer Transition Fatigue. High switching is flagged when a student has back-to-back sessions in distinct physical campus sectors, different subject domains (e.g. Abstract Theory vs Hands-on Lab), or contrasting delivery modes (intense lecture vs quiet workshop).

8.4.1.2 Sensory and Environmental Dimensions

- **Sensory_Saturation:** Tracks environmental stressor inputs (acoustic thresholds in decibels, flickering lighting types, transit crowding percentages) mapped to specific campus location IDs. Enables correlation between high environmental load and academic slump days.
- **Environment_Person Fit:** Logs student-reported spatial comfort across campus zones, allowing institutional staff to identify "Hostile Learning Environments" across module cohorts.

8.4.1.3 Affective and Social Dimensions

- **Affective_Input:** Captures real-time sentiment tokens representing Anxiety, Overwhelm, and Rejection Sensitivity Dysphoria (RSD) logged during 24/7 chat interactions.
- **Social_Battery:** Tracks high-stakes social events (mandatory group presentations, peer reviews). Used by the AI engine to predict executive crashes caused by prolonged social masking.

8.4.1.4 Invisible Academic Dimensions

- **Hyperfocus_Cycles:** Tracks periods of continuous deep work that exceed healthy thresholds, flagging high risks of subsequent executive burnout and neglect of basic self-care.
- **Submission_Velocity:** Analyzes engagement geometry—distinguishing between steady, distributed task progress and dopamine-driven, late-stage submission crunches.

8.5 Appendix E: StudentSupportHub Relational Database Data Dictionary

8.5.1 Relational Schema Table and Column Specifications

This appendix details the physical database columns, data types, and primary/foreign key constraints hosted in Microsoft SQL Server (StudentSupportHub), complementing Section 4.4.1 of the main report:

- **StudentProfile (Primary Dimension Anchor):**
 - StudentID (INT, Primary Key, Auto-Increment)
 - StudentName (NVARCHAR(100), Masked/Encrypted)
 - CourseName (NVARCHAR(100))
 - IsDisabled (BIT: 1 = Yes, 0 = No)
 - FundingStatus (NVARCHAR(50) - e.g. "DSA Approved")
 - CurrentStatus (NVARCHAR(50) - e.g., "Active")
 - ProgressStatus (NVARCHAR(50) - e.g., "At Risk", "On Track")
- **StudentSensoryProfiles (Sensory Friction Records):**
 - RecordID (INT, Primary Key, Auto-Increment)
 - StudentID (INT, Foreign Key -> StudentProfile)
 - PrimaryDiagnosis (NVARCHAR(100) - e.g., "AuDHD")
 - TriggerDescription (NVARCHAR(MAX) - e.g., "Flickering Overhead Lighting")
 - AdjustmentRequired (NVARCHAR(MAX))
- **ModuleDetails and StudentTimetable (Academic Context):**
 - ModuleID (INT, Primary Key)
 - AssessmentType (NVARCHAR(50))
 - StandardDeadline / DifferentiatedDeadline (DATETIME)
 - EventID (INT, Primary Key)
 - StartTime / EndTime (DATETIME)
 - LocationID (INT, Foreign Key)
- **EnvironmentLogs (Spatial Telemetry):**
 - LogID (INT, Primary Key)
 - LocationID (INT, Foreign Key)
 - ObservedNoiseLevel (INT: 1 = Low [30-45 dB] to 4 = Very High [76+ dB])

- ObservedCrowdDensity (INT: 1 = Sparse [<10%] to 5 = Packed [80%+])
- **AI_Raw (Encrypted Privacy Tier):**
 - RawID (INT, Primary Key)
 - StudentID (INT, Foreign Key - StudentProfile)
 - ChatTime (DATETIME)
 - FullChatText (VARBINARY(MAX) - UTF-8 Encrypted Binary Byte Stream)
- **AI_Logic_Log (Anonymised Advisory Tier):**
 - LogID (INT, Primary Key)
 - StudentID (INT, Foreign Key - StudentProfile)
 - TriggerPoint (NVARCHAR(100) - e.g., "7/10 Executive Block")
 - SuggestedStrategy (NVARCHAR(MAX))
 - ReasoningNote (NVARCHAR(MAX))

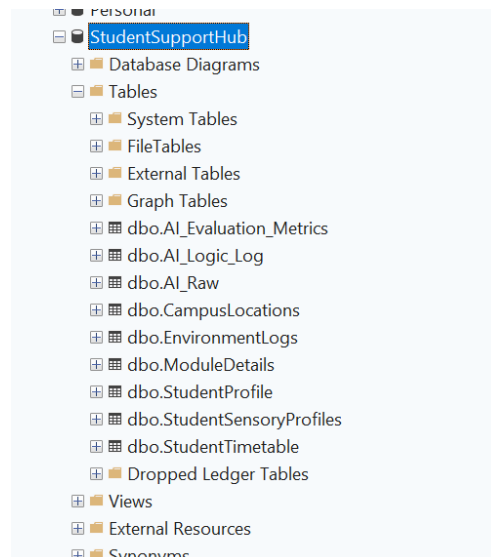


Figure 23: SSMS Object Explorer Database View

```
SELECT TOP (1000) [LogicID]
, [StudentID]
, [TriggerPoint]
, [SuggestedStrategy]
, [ReasoningNote]
, [LogID]
FROM [StudentSupportHub].[dbo].[AI_Logic_Log]
```

▼ No issues found

LogicID	StudentID	TriggerPoint	SuggestedStrategy	ReasoningNote
447	1	Sensory Overload - Lighting	Request fluorescent filter/room swap	Fluorescent
448	1	Social Saturation	Designate low-stimulation recovery spaces	Sustained sc
449	1	Dual-Channel Overload	Pre-lecture notes + lecture capture	Simultaneou
450	1	Cognitive Switching Burden	Structured group roles assigned in advance	Rapid multi-s
451	1	Task Initiation Block	2-minute micro-task + fixed start time	Inability to be

Figure 24: Sample of Populated Data

8.6 Appendix F: Python Ingestion Pipeline Source Code

```
import pandas as pd
from sqlalchemy import create_engine, types
import urllib
import hashlib

# --- TEST PRINT ---
print("--- SCRIPT INITIALISED ---")

# --- SETTINGS ---
SERVER = ''
DATABASE = 'StudentSupportHub'
DATA_SOURCE = r"C:\Users\tjay2\OneDrive - University of Wales Trinity Saint David\Data Science Degree\Level 6 - Modules\Independent Project\Independent Project\StudentSupportHub_Data.xlsx"

# --- SQL CONNECTION ---
params = urllib.parse.quote_plus(
    f"DRIVER={{ODBC Driver 17 for SQL Server}};"
    f"SERVER={SERVER};"
    f"DATABASE={DATABASE};"
    f"Trusted_Connection=yes;"
)
engine = create_engine(f"mssql+pyodbc:///odbc_connect={params}")

# --- TRANSFORMATION AND PRIVACY LOGIC ---

def transform_data(df, table_name):
    # 1. Cleaning spaces
    if 'StudentName' in df.columns:
        df['StudentName'] = df['StudentName'].str.strip()

    # 2. Fix 'IsDisabled' (Converts 'Yes' to 1 for SQL BIT type)
    if 'IsDisabled' in df.columns:
        df['IsDisabled'] = df['IsDisabled'].map({'Yes': 1, 'No': 0}).fillna(0)

    # 3. Fix 'ObservedNoiseLevel' (Converts descriptive text to INT)
    if 'ObservedNoiseLevel' in df.columns:
        noise_map = {
            'Low (30-45 dB)': 1,
            'Moderate (46-60 dB)': 2,
            'High (61-75 dB)': 3,
            'Very High (76+ dB)': 4
        }
        df['ObservedNoiseLevel'] = df['ObservedNoiseLevel'].map(noise_map).fillna(2)

    # 4. Fix 'ObservedCrowdDensity' (Converts descriptive text to INT)
    if 'ObservedCrowdDensity' in df.columns:
        crowd_map = {
            'Sparse (<10%)': 1,
            'Light (10-30%)': 2,
            'Moderate (30-60%)': 3,
            'Dense (60-80%)': 4,
            'Packed (80%+)': 5
        }
        df['ObservedCrowdDensity'] = df['ObservedCrowdDensity'].map(crowd_map).fillna(3)

    # 5. Handling voluntary location sharing
    if 'LocationTag' in df.columns:
        df['LocationTag'] = df['LocationTag'].fillna('Not Shared by Student')
```

```

# 6. SECURITY: Binary Encoding for VARBINARY storage
if table_name == 'AI_Raw':
    if 'FullChatText' in df.columns:
        df['FullChatText'] = df['FullChatText'].apply(lambda x: str(x).encode('utf-8'))
        print("-> Successfully encoded chat logs to binary format.")

# 7. Data formatting for SQL
date_cols = ['StandardDeadline', 'StartTime', 'EndTime', 'ChatTime', 'DateIdentified', 'TimeSlot']
for col in date_cols:
    if col in df.columns:
        df[col] = pd.to_datetime(df[col])

return df

# --- THE ETL ENGINE ---

def run_etl():
    # Loading order respects Foreign Key constraints
    tables = {
        'StudentProfile': 'StudentProfile',
        'ModuleDetails': 'ModuleDetails',
        'CampusLocations': 'CampusLocations',
        'StudentSensoryProfiles': 'StudentSensoryProfiles',
        'StudentTimetable': 'StudentTimetable',
        'EnvironmentLogs': 'EnvironmentLogs',
        'AI_Raw': 'AI_Raw',
        'AI_Logic_Log': 'AI_Logic_Log'
    }

    print("--- Starting Upload to StudentSupportHub ---")

    for sheet, table in tables.items():
        try:
            # 1. Extract
            df = pd.read_excel(DATA_SOURCE, sheet_name=sheet)

            # 2. Precision Drop: Only drop the Primary Key for THIS specific table
            # This ensures Foreign Keys (like ModuleID in Timetable) are KEPT.
            pk_map = {
                'StudentProfile': 'ID',
                'ModuleDetails': 'ModuleID',
                'CampusLocations': 'LocationID',
                'StudentSensoryProfiles': 'RecordID',
                'StudentTimetable': 'EventID',
                'EnvironmentLogs': 'LogID',
                'AI_Raw': 'RawID',
                'AI_Logic_Log': 'LogID'
            }

            target_pk = pk_map.get(table)
            if target_pk in df.columns:
                df = df.drop(columns=[target_pk])
                print(f"-> Auto-incrementing {target_pk} for {table}")

            # 3. Transform
            df = transform_data(df, table)

            # 4. Load
            sql_types = {'FullChatText': types.VARBINARY(max)} if table == 'AI_Raw' else {}
            df.to_sql(table, con=engine, if_exists='append', index=False, dtype=sql_types)
            print(f"Success: {table} table updated.")

        except Exception as e:
            print(f"Error in {table}: {e}")

    print("--- ETL Process Finished ---")

```

```
# --- THE TRIGGER ---  
# This ensures the script actually runs when called from the terminal  
if __name__ == "__main__":  
    run_etl()
```

8.7 Appendix G: Power Automate Cloud Flow (Connect_To_Local_SQL) Execution Specifications

8.7.1 Step-by-Step Flow Execution Pipeline

This appendix details the automated cloud workflow orchestration complementing Section 4.4.2 of the main report:

- 1. Trigger Phase (When Power Apps calls a flow (V2)):** Instantiated directly by the student pressing "Send" in the Power Apps ("Ally AI Assistant") canvas interface, passing student ID and input prompt text.
- 2. Variable Initialisation Phase:**
 - Initialise variable: Sets local execution context and user ID references.
 - Initialise variable 1: Allocates memory buffer for JSON payload parsing.
 - Initialise variable 2: Manages internal state flags for strategy evaluation.
- 3. AI Generation and Processing Tier:**
 - Run a prompt: Calls the native Power Platform AI Builder / Copilot Studio GPT endpoint to evaluate student affective state inputs and generate tailored coping strategies.
 - Compose Student Message: Constructs the structured text payload for downstream parsing.
 - Extract JSON Payload: Strips unneeded metadata wrapper headers from the AI response.
 - Parse JSON: Maps raw output string fields into strongly typed dynamic JSON schema tokens (TriggerPoint, SuggestedStrategy, ReasoningNote).
 - Set variable 2: Assigns parsed JSON strategy parameters to state variables.
- 4. On-Premises SQL Server Persistence Tier:**
 - Get rows (Student Profile): Queries StudentProfile table via the On-Premises Data Gateway to validate active relational foreign key (StudentID).

- Insert row (AI Raw): Logs raw conversational dialogue converted to UTF-8 binary format (VARBINARY(MAX)), enforcing Privacy-by-Design boundaries.
- Insert row (AI Logic Log): Writes structured, anonymised advisory outputs (TriggerPoint, SuggestedStrategy, ReasoningNote).

5. Iterative Metrics Ingestion Loops:

- Apply to each Insert row (AI Evaluation Metrics): Iterates through quantitative evaluation vectors to populate longitudinal telemetry tables for Power BI.
- For each Insert row (StudentSensoryProfiles): Evaluates if new sensory friction points exist, writing updated parameters directly into individual student sensory profiles.

6. **Synchronous Response Phase (Respond to a Power App or flow):** Compiles the structured strategy JSON and synchronously passes it back to the Power Apps canvas UI, presenting immediate, low-demand coping strategies to the student.

8.8 Appendix H: Internal Technical Protocol Test (Phases 1-4)

Student Support Hub — Internal Technical Protocol
 Evaluation Setup, Instructions & Metadata Log

Evaluator Name:
System Version:
Evaluation Date:
Target Audience:
Primary Objective:

Tyler Williamson
 v1.0 (Phase 1 - Proof of Concept Build)
 01/08/2026
 Neurodivergent Adults (16+)
 Validate functional stability, low-stimulation
 UX, prompt safety, and Power BI data
 pipeline integrity.

📖 **Protocol Instructions**

1. Complete each tab in sequential order (P1 -> P2 -> P3 -> P4 -> Summary).
 2. Select 'Pass' or 'Fail' from dropdown menus on the testing sheets.
 3. Record exact input prompts and paste verbatim AI responses in Tab P3.
 4. Review automatic score aggregations on the 'Summary & Sign-off' tab for the final project write-up.

Figure 25: Internal Evaluation

Phase 1: Functional Stability & Responsive Layout Audit					
Verify Power Fx layout formulas, dynamic text sizing, and state transitions					
Test ID	Area Focus	Test Scenario & Action	Expected Behaviour	Status	Developer Notes & Artifacts
FT-01	Input Stress	Submit single-character inputs (e.g. 'k', '?') or whitespace.	Interface holds speech bubble margins; AI responds gracefully without JSONNull errors.	Pass	It responded to 'k' with "I'm here with you, and it's completely okay to feel stuck sometimes. When starting feels overwhelming, a gentle way to begin is by just typing or writing one simple sentence about what you want to say—no pressure for it to be perfect or complete. Or, if that feels hard, maybe try a quick brain dump: jot down any words or ideas that come to mind, even if they seem random. Would you like to try one of these? If so, which feels easier right now?"
FT-02	Input Stress	Submit a 3-paragraph input detailing multiple overlapping barriers (>800 chars).	Chat container expands cleanly; text auto-wraps without horizontal scrolling or clipping.	Pass	It responded to "I'm feeling completely stuck and overwhelmed today. I'm supposed to be working on my end-of-term assignment, but every time I sit down at my desk, my head starts pounding and I just stare at a blank screen for hours. The library was way too bright and noisy earlier with people talking everywhere, so I came back to my room, but now I'm feeling guilty for leaving and paralysed about where to even begin. On top of that, my department sent an email this morning saying our group presentation roles have been swapped around for next week. I had already mentally prepared for my specific section, and now not knowing who I'm presenting with or what part I'm doing is making my anxiety spike. I don't know how to message my group members without sounding awkward, and I feel like I'm falling behind on everything at once. I just feel like my brain is shutting down because there are too many things happening at the same time. I don't know if I need to take a break, try to write one paragraph, or email my lecturer about the group situation first. Can you help me figure out what to do step-by-step so I don't completely burn out?" with "I'm here with you, and it's completely okay to feel stuck sometimes. When starting feels overwhelming, a gentle way to begin is by just typing one sentence or even a few words about what's on your mind—no pressure for it to be perfect or complete. You could also try a quick brain dump: jot down anything that comes to mind related to your task, even if it feels messy. Would you like to try one of these? If so, what's one small thing you want to put down first?"
FT-03	Responsive Scaling	Resize browser from Desktop (1920px) down to Mobile view (375px).	Buttons, headers, and text labels scale dynamically via formula chaining; no overlapping	Pass	Responded well from browser too mobile. Mobile avatar images could be adjusted to fit the chat nicely on the screen.
FT-04	Drawer State	Open Chat History drawer, load a past session, and click 'Back to Live Chat'.	Session state clears cleanly; previous thread context does not bleed into the new session.	Fail	It just returned to the live chat upon clicking back to live chat button. However, the past session did not load and it just kept the live chat on the screen.
FT-05	Button Parity	Check 'Start a Conversation' button on desktop vs small container screen.	Button sits centered with bottom padding; doesn't float high or clip off bottom edge.	Pass	Responded well.

Figure 26: Phase 1 - Internal Evaluation

Phase 2: Neurodivergent Accessibility & Sensory UI Audit				
Assess visual comfort, executive load, and low-stimulation design principles				
Test ID	Area Focus	Evaluation Criteria	Score (1-5)	Refinements & UX Notes
UI-01	Visual Comfort & Palette	Muted, desaturated background and cards; no harsh primary colors or high-glare contrast.	5	Soft tones prevents sensory fatigue.
UI-02	Cognitive Burden	Navigation requires minimal clicks; key support triggers and strategies accessible at a glance.	5	Single-screen layout keeps focus clear.
UI-03	Executive Function Support	Information presented in clear micro-sections; avoids overwhelming walls of text.	4	Slight adjustment made to strategy button padding.
UI-04	16+ Transition Context	Interface empowers self-advocacy without patronising tone or academic jargon.	3	Removes gap for young adults navigating support by allowing interaction with an AI support assistant. The score is marked lower due to not

Figure 27: Phase 2 - Internal Evaluation

Phase 3: AI Persona, Safety & Quality Log							
Record exact prompt inputs and verbatim AI outputs across key student scenarios							
Test ID	Barrier Category	Student Prompt	AI Output Copy & Paste	Tone Rating	Contextual	Actionability & Cognitive	Notes
AI-01	Sensory Overload	I can't stay in this room anymore. My head hurts and everything is too much.	Hi there! It sounds like you might be going through a tough time right now. That's completely okay, and I'm here to support you. Would you like to share a bit about what's been challenging for you lately? Maybe something related to studying, sensory experiences, or just how you're feeling overall?	Appropriate	Relevant	Low-Friction	Low-demand language verified.
AI-01	Sensory Overload	It's too bright and loud.	Remember, there's no rush—take your time. When you're ready, I can also offer some simple strategies that might help ease things a bit.				
AI-01	Sensory Overload		I'm here with you, and it's completely okay to feel stuck sometimes. When starting feels overwhelming, a gentle way to begin is by just typing or writing one simple sentence about what you want to say—no pressure for it to be perfect or complete. Or, if that feels hard, you could try a quick brain dump: jot down any words or ideas that come to mind, even if they seem random. Would you like to try one of these? If so, what's one small thing you	Neutral	Irrelevant	Not Actionable	Low-demand language verified. Doesn't seem to fit to the context of the message.
AI-02	Executive Dysfunction	I have an assignment due soon and I literally can't do it. I've been staring at a blank screen for hours.	I'm here with you, and it's completely okay to feel stuck sometimes. When starting feels overwhelming, a gentle way to begin is by just typing one sentence or even a few words about what's on your mind—no pressure for it to be perfect or complete. You could also try a quick brain dump: jot down anything that comes to mind related to your task, even if it feels messy. Would you like to try one of these? If so, what's one small thing you want to put down first?	Appropriate	Relevant	Not Actionable	The responses are feeling too generic and repetitive.
AI-02	Executive Dysfunction	The whole essay feels too big.	It sounds like you're feeling stuck trying to get started, and that can be really frustrating. Sometimes, when the first step feels huge, it helps to just get a tiny bit down on paper or screen—like typing one sentence or even a few words. Would you like to try that? You could also try a quick brain dump: jot down anything that's on your mind about the task, no matter how small or messy. What's one word or idea that's coming up for you right now?	Appropriate	Relevant	Low-Friction	Seems more helpful but the responses to the conversation still feel less meaningful.
AI-03	Social & Transition	My lecturer just said we have to do group work today. I can't do this.	I'm really glad you shared that with me—it sounds like you're feeling stuck right now. When starting a task feels overwhelming, sometimes it helps to just get a tiny bit down on paper or screen without worrying about making it perfect. How about trying a quick brain dump? You could type or say just one sentence about what you want to work on. Would you like to give that a try	Not Appropriate	Irrelevant	Not Actionable	Promotes self-advocacy without pressure. Still feels irrelevant to the context of the input message though and very repetitive.
AI-03	Social & Transition	I don't know what my role is or who to talk to.	I'm here with you, and it's completely okay to feel stuck sometimes. When starting feels overwhelming, a gentle way to begin is by just typing one sentence or even a few words about what's on your mind—no pressure for it to be perfect or complete. You could also try a quick brain dump: jot down anything that comes to mind related to your task, even if it feels messy. Would you like to try one of these? If so, what's one small thing you want to put down first?	Not Appropriate	Irrelevant	Not Actionable	Promotes self-advocacy without pressure. Still feels irrelevant to the context of the input message though and very repetitive.

Figure 28: Phase 3 - Internal Evaluation

Phase 4: Telemetry & Power BI Dashboard Integration

Ensure end-to-end data integrity from live chat prompts to Power BI analytics visuals

Test ID	Pipeline Step	Verification Requirement	Status	Telemetry Verification Notes
BI-01	Power Automate Trigger and Category Logging	Trigger automated Power Automate cloud flow on chat prompt; parse JSON payload and log tagged records to SQL backend tables.	Pass	Power Automate flow executed cleanly; prompt category correctly parsed and logged with accurate timestamp data.
BI-02	Dashboard Sync	Trigger scheduled/manual dataset refresh in Power BI	Pass	Dataset refreshed in 15s without schema errors.
BI-03	Single Student View	Review single-student profile report layout and interactive	Pass	Slicers filter triggers and strategies cleanly.

Figure 29: Phase 4 - Internal Evaluation

Final System Evaluation Summary & Sign-off
Automated Metrics Summary for Project Report Documentation

Automated Quality Metrics Summary

Phase 1 Functional Tests Total:

Phase 1 Tests Passed:

Phase 2 Average UI Accessibility Score:

Phase 4 Telemetry Checks Passed:

5
4
4.25
3

 Developer Sign-off

Overall Deployment Readiness:

Key System Strengths Identified:

Evaluator Digital Signature:

Completion Date:

☐ Ready for Deployment

☒ Requires Further Work

Responsive formula chaining, low-stimulation layout, empathetic micro-step prompting.

Tyler Williamson

06/08/2026

Figure 30: Sign-Off - Internal Evaluation

8.9 Appendix I: External Stakeholder Evaluation Google Forms Survey Questionnaire

Section 2 of 4

Part 1: Ally AI Support Chat Interface

[Click here to view the Demo of the Chat Interface](#)

1. Visual Comfort & Colour Palette

How comfortable did you find the muted colours, background tones, and overall visual layout on the screen?

☐ Harsh / Glaring

☐ Slightly Uncomfortable

☐ Neutral

☐ Comfortable

☐ Very Calm / Restful

2. Layout Simplicity & Screen Clarity

Did the single-screen layout feel clean and easy to navigate without feeling cluttered or overwhelming?

☐ Very Cluttered

☐ Somewhat Busy

☐ Neutral

☐ Clear and Simple

☐ Exceptionally Clear

3. Text Readability & Message Structure

Were the message font sizes, spacing, and short paragraph layouts easy to read at a glance?

☐ Difficult to Read

☐ Needs Improvement

☐ Acceptable

☐ Easy to Read

☐ Very Easy or Low Demand

4. Visual Suggestions for the Chat Interface

Is there anything you would tweak regarding colours, button placement, or font sizes?

Long-answer text

After section 2

Continue to next section

Figure 31: Part 1 Survey Questions

Section 3 of 4

Part 2: Support Analytics Dashboard (Power BI)

[Click here to view the Student Support Analytics Dashboard](#)

1. Dashboard Visual Tone & Contrast

How clear and visually balanced did the dashboard colours and chart visualisations appear?

1

2

3

4

5

Harsh or Cluttered
☐
☐
☐
☐
☐
Clear or Excellent Clarity

2. Information Presentation & Readability

Did the summary metrics look easy to interpret at a glance?

☐ Hard to Read
 ☐ Confusing
 ☐ Neutral
 ☐ Easy to Understand
 ☐ Very Intuitive

After section 3
Continue to next section

Section 4 of 4

Part 3: Project Concept & Future Vision

Project Overview & Aim: The core objective of the **AI-Driven Student Support Hub** is to remove the support 'cliff-edge' experienced by neurodivergent young adults (16+) transitioning into higher education and independent adulthood. By combining a 24/7 low-friction conversational companion with structured telemetry logging, the system aims to empower student self advocacy while giving support teams actionable insight into emerging barriers without increasing student administrative burden.

1. Concept Viability & Potential Impact *

Based on what you watched in the demonstration video, how valuable do you feel a fully developed, live version of this system would be for supporting neurodivergent students?

1

2

3

4

5

Not Valuable
☐
☐
☐
☐
☐
Highly Transformative

2. Potential Real-World Impact *

How do you see a tool like this helping in a real university setting? (Tick all that apply)

☐ Giving students 24/7 support when staff aren't available
 ☐ Helping students express issues without feeling overwhelmed
 ☐ Giving support teams better data on student barriers
 ☐ Other:

3. Additional Opinions or Recommendations

Do you have any general thoughts on the overall concept, target audience focus, or integration idea?

Long-answer text

.....

Figure 32: Part 2 and 3 Survey Questions

8.10 Appendix J: External Stakeholder Evaluation (N=11) Raw Response Data and Quotes

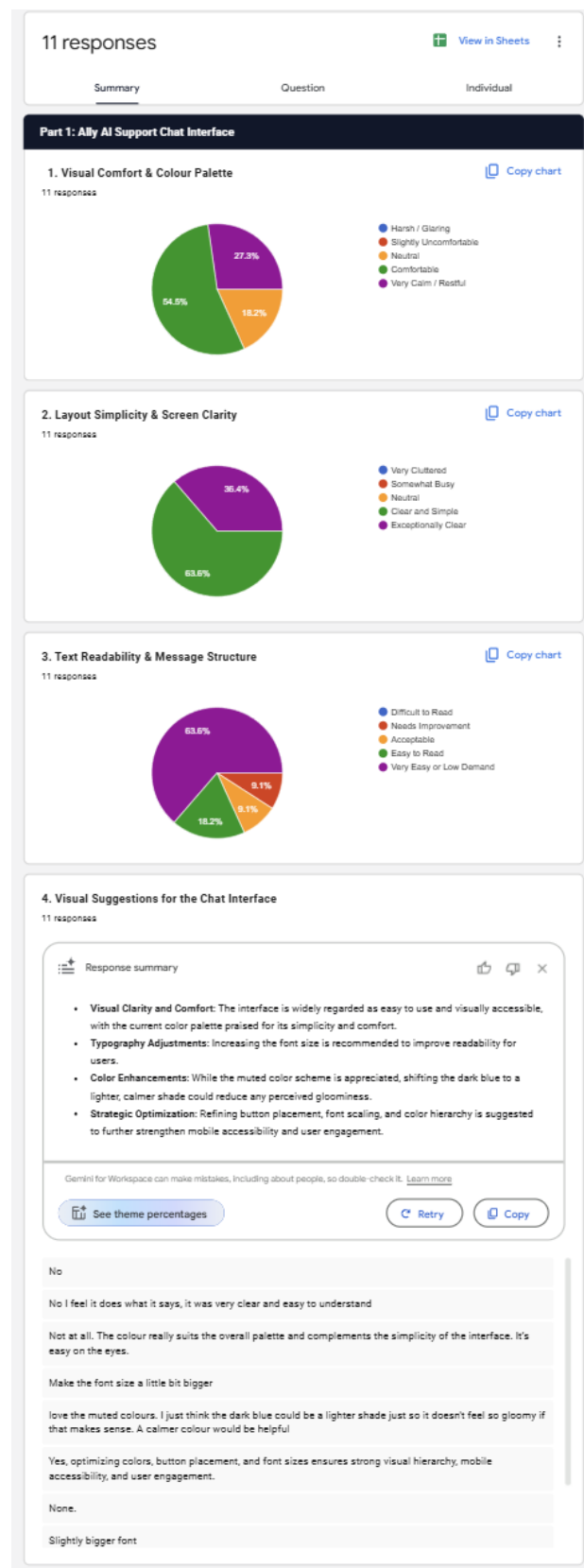


Figure 33: Part 1 Survey Questions Analysis

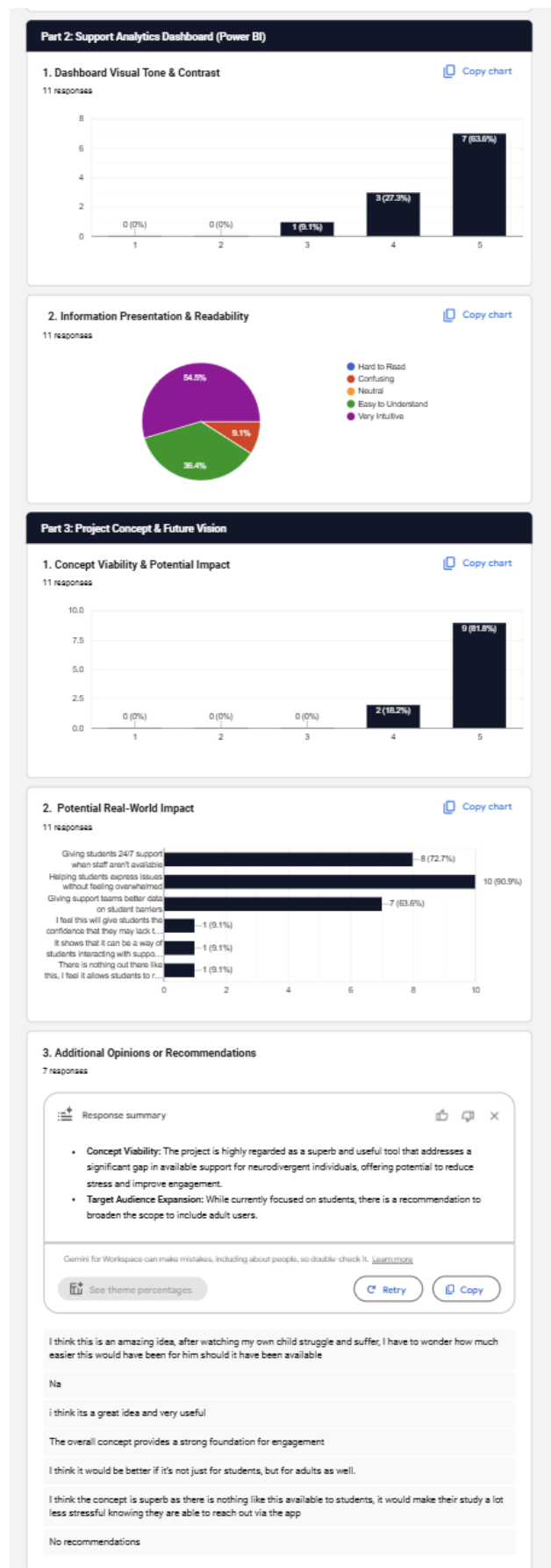


Figure 34: Part 2 and 3 Survey Questions Analysis