TRANSFORMING UNIVERSITY MENTAL HEALTH SUPPORT: AN AGENTIC AI FRAMEWORK FOR PROACTIVE INTERVENTION AND RESOURCE MANAGEMENT

BACHELOR’S THESIS

THE SUSTAINABLE DEVELOPMENT GOALS
Industry, Innovation and Infrastructure
Affordable and Clean Energy
Climate Action

Written by:

GIGA HIDJRIKA AURA ADKHY
21/479228/TK/52833

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TRANSFORMING UNIVERSITY MENTAL HEALTH SUPPORT: AN AGENTIC AI FRAMEWORK FOR PROACTIVE INTERVENTION AND RESOURCE MANAGEMENT

THESIS

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Written by:

GIGA HIDJRIKA AURA ADKHY
21/479228/TK/52833

Has been approved and endorsed

on . . . . . .

Supervisor I	Supervisor II
Dr. Bimo Sunarfri Hantono, S.T., M.Eng.	**Guntur Dharma Putra, PhD**
NIP 197701312002121003	**NIP 111199104201802102**

STATEMENT

Saya yang bertanda tangan di bawah ini :

Name	: Giga Hidjrika Aura Adkhy
NIM	: 21/479228/TK/52833
Tahun terdaftar	: 2021
Program	: Bachelor's degree
Major	: Information Engineering
Faculty	: Faculty of Engineering, Universitas Gadjah Mada

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Tuliskan kepada siapa skripsi ini dipersembahkan!

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PREFACE

Contoh: Puji syukur ke hadirat Allah SWT atas limpahan rahmat, karunia, serta petunjuk-Nya sehingga tugas akhir berupa penyusunan skripsi ini telah terselesaikan dengan baik. Dalam hal penyusunan tugas akhir ini penulis telah banyak mendapatkan arahan, bantuan, serta dukungan dari berbagai pihak. Oleh karena itu pada kesempatan ini penulis mengucapkan terima kasih kepada:

1. Orang 1 yang telah
2. Orang 2 yang telah
3. <isi dengan nama orang lainnya>

Akhir kata penulis berharap semoga skripsi ini dapat memberikan manfaat bagi kita semua, aamiin.

Catatan: setiap nama yang dituliskan boleh disertai dengan alasan berterima kasih.

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NOMENCLATURE AND ABBREVIATION

[SAMPLE]

b	=	bias
$K(x_i, x_j)$	=	fungsi kernel
y	=	kelas keluaran
C	=	parameter untuk mengendalaikan besarnya pertukaran antara penalti variabel slack dengan ukuran margin
L_D	=	persamaan Lagrange dual
L_P	=	persamaan Lagrange primal
$\mathbf{w}$	=	vektor bobot
$\mathbf{x}$	=	vektor masukan
ANFIS	=	Adaptive Network Fuzzy Inference System
ANSI	=	American National Standards Institute
DAG	=	Directed Acyclic Graph
DDAG	=	Decision Directed Acyclic Graph
HIS	=	Hue Saturation Intensity
QP	=	Quadratic Programming
RBF	=	Radial Basis Function
RGB	=	Red Green Blue
SV	=	Support Vector
SVM	=	Support Vector Machines

INTISARI

Layanan kesejahteraan mahasiswa di perguruan tinggi masih banyak bersifat reaktif dan sering terlambat menjangkau mereka yang membutuhkan. Skripsi ini merancang dan mengevaluasi sebuah kerangka multi-agen AI yang berorientasi keselamatan untuk mendukung layanan yang lebih proaktif dan terukur dengan tetap melibatkan manusia. Artifak inti, *Safety Agent Suite*, terdiri dari lima komponen: (i) **Safety Triage Agent** untuk penyaringan risiko dan eskalasi, (ii) **Support Coach Agent** yang memberikan intervensi singkat berlandaskan CBT, (iii) **Service Desk Agent** untuk tindak lanjut operasional, (iv) **Insights Agent** untuk analitik agregat yang menjaga privasi guna perbaikan layanan, dan (v) **Aika Meta-Agent** yang mengkoordinasikan keempat agen spesialis tersebut dengan orkestrasi berbasis peran untuk memastikan interaksi yang koheren dan mengutamakan keselamatan.

Kami membangun prototipe fungsional dalam platform UGM-AICare dan melakukan evaluasi berbasis skenario yang menitikberatkan secara eksklusif pada kinerja arsitektur agen: sensitivitas/spesifisitas triase pada skenario krisis sintetis; keandalan orkestrasi melalui tingkat keberhasilan pemanggilan fungsi dan transisi state; latensi ujung-ke-ujung; ketahanan terhadap *prompt injection*; serta kualitas coaching yang dinilai buta menggunakan rubrik kepatuhan CBT. **Skripsi ini berfokus secara spesifik pada desain dan evaluasi kerangka multi-agen itu sendiri**—agen spesialis berbasis BDI, lapisan orkestrasi Aika, dan perilaku kolektif mereka dalam konteks percakapan kritis keselamatan. Desain basis data, komponen antarmuka pengguna, dan infrastruktur deployment didokumentasikan sebagai konteks implementasi namun bukan subjek evaluasi formal. Hasil menunjukkan kelayakan orkestrasi agen yang andal dengan latensi terkendali dan moda kegagalan yang dapat dipantau di bawah pengawasan manusia. Kami membahas pertimbangan etis, prinsip *privacy by design*, keterbatasan penelitian, dan kebutuhan studi klinis lapangan di masa depan dengan pengguna riil.

Kata kunci: Sistem Multi-Agen; Arsitektur BDI; Orkestrasi Agen; Triase Keselamatan; LangGraph; Human-in-the-Loop; Kesejahteraan Mahasiswa; Evaluasi Berbasis Skenario

ABSTRACT

Higher Education Institutions face rising demand for student well-being support while operating largely reactive, high-friction service models. This thesis proposes and evaluates a safety-oriented, multi-agent AI framework that coordinates specialized agents to enable proactive, scalable support under human oversight. The core artifact, the Safety Agent Suite, comprises: (i) a Safety Triage Agent for risk screening and escalation, (ii) a Support Coach Agent delivering brief CBT-informed micro-interventions, (iii) a lightweight Service Desk Agent for operational follow-ups, and (iv) an Insights Agent for privacy-preserving aggregate analytics to inform service improvement, all coordinated through (v) an Aika Meta-Agent that provides unified, role-based orchestration. The multi-agent system is built with LangGraph and includes guardrails for tool use, redaction, and auditability.

We implement a functional prototype within the UGM-AICare platform and conduct scenario-based evaluations focused exclusively on agent architecture performance: triage sensitivity/specificity on synthetic crisis scenarios; orchestration reliability via tool-call success and state transition behavior; end-to-end latency; robustness against prompt-injection; and coaching quality via CBT adherence rubrics with blinded human ratings. **This thesis focuses specifically on the design and evaluation of the multi-agent framework itself**—the BDI-based specialist agents, Aika orchestration layer, and their collective behavior in safety-critical conversational contexts. Database design, user interface components, and deployment infrastructure are documented as implementation context but are not subjects of formal evaluation. Results demonstrate the feasibility of reliable agent orchestration with bounded latency and controllable failure modes under human-in-the-loop supervision. We discuss ethical considerations, privacy by design principles, research limitations, and outline requirements for future clinical field studies with real users.

Keywords: Multi-Agent Systems; BDI Architecture; Agent Orchestration; Safety Triage; LangGraph; Human-in-the-Loop; Student Well-being; Scenario-Based Evaluation

CHAPTER I
INTRODUCTION

1.1 Background

Higher Education Institutions (HEIs) are facing a critical and growing challenge in supporting student well-being [1,2]. A landmark report highlights the escalating prevalence of mental health and substance use issues among student populations, urging institutions to adopt a more comprehensive support model [3]. This crisis not only jeopardizes students' academic success and personal development but also places an immense, unsustainable strain on the institutions tasked with supporting them. Recent global surveys indicate that nearly 42% of university students meet the criteria for at least one mental health disorder, while the average counselor-to-student ratio in higher education remains around 1:1,500, well above recommended levels for effective service delivery [4, 5].

The traditional support model, centered around on-campus counseling services, is fundamentally **reactive**. It relies on students to self-identify their distress and navigate the process of seeking help. This paradigm faces significant operational challenges, including insufficient staffing, long waiting lists, and an inability to provide immediate, 24/7 support, which ultimately limits access for a large portion of the student body [6]. Consequently, a critical gap persists between the need for mental health services and their actual provision, leaving many students without timely support [7].

To bridge this gap, a paradigm shift from a reactive to a **proactive** support model is imperative [7]. The engine for this evolution is **Digital Transformation**, a process that leverages technology to fundamentally reshape organizational processes and enhance value delivery within HEIs [8]. Within this context, Artificial Intelligence (AI) has emerged as a key enabling technology, with systematic reviews confirming its significant potential to analyze complex data, automate processes, and deliver personalized interventions at scale within the higher education landscape [9, 10].

However, most existing AI applications in university mental health remain limited to passive chatbots or predictive dashboards that, while insightful, depend on human operators to interpret and act upon their outputs, a limitation widely recognized as the *insight-to-action gap* [11, 12]. This thesis argues that overcoming this gap requires a more autonomous paradigm, in which AI systems do not merely predict or inform but can proactively decide and act.

This research therefore moves beyond conventional AI applications by proposing the use of **Agentic AI**. An intelligent agent is an autonomous system capable of perception, decision-making, and proactive action to achieve specific goals [13,14], representing a new frontier in educational technology [15]. We propose that a framework built upon a system of collaborative intelligent agents, a **Multi-Agent System (MAS)**, can create a truly transformative ecosystem. Such a system would not only serve as a support tool for students but, more importantly, would function as a strategic asset for the institution, enabling data-driven decision-making, automating operational workflows, and facilitating a proactive stance on student well-being.

This framework is prototyped within the **UGM-AICare Project**, a collaborative university research initiative focused on developing AI-driven mental health and well-being tools for the Universitas Gadjah Mada (UGM) community. The project serves as the practical testbed for validating the proposed agentic system in a real institutional context.

1.2 Problem Formulation

The inefficiency and reactive nature of current university mental health support systems present a complex problem. To move towards a proactive and scalable model, this research addresses the following core challenges:

1. The primary challenge is the **design of a cohesive, safety-oriented agentic AI framework** capable of automating key institutional processes. This requires a shift from a monolithic chatbot to a multi-agent system where specialized agents handle distinct tasks, including real-time crisis detection, personalized coaching, clinical case management, and privacy-preserving analytics.
2. The technical challenge of **orchestrating a heterogeneous multi-agent system** in a robust, scalable, and secure cloud-native architecture. This involves managing stateful, long-running interactions and ensuring reliable communication between agents powered by external, non-deterministic LLMs.
3. The methodological challenge of **validating the framework's functional capabilities and potential for impact in the absence of a full-scale clinical trial**. This requires developing meaningful, scenario-based testing protocols that can effectively demonstrate the agentic workflows and their advantages over static systems.

To address these challenges, this thesis proposes and details the **Safety Agent Suite**, a framework comprised of four specialized, collaborative intelligent agents—a **Safety Triage Agent (STA)**, a **Support Coach Agent (SCA)**, a **Service Desk Agent (SDA)**, and an **Insights Agent (IA)**—coordinated through an **Aika Meta-Agent** that provides unified, role-based orchestration and ensures coherent, safety-first interactions across all user roles.

1.3 Objectives

The primary objectives of this thesis are:

1. To design an agentic AI framework, grounded in the BDI model of rational agency, that systematically bridges the 'insight-to-action' gap in institutional mental health support.
2. To implement a functional proof-of-concept prototype, the 'Safety Agent Suite,' demonstrating the orchestration of specialized agents (triage, coaching, service desk, insights) and a meta-agent coordinator using LangGraph.
3. To evaluate the prototype's core agentic workflows through scenario-based testing, validating its capacity for proactive intervention and automated administrative action.

1.4 Research Questions

To keep the scope concrete and measurable, this thesis addresses the following research questions (RQs):

1. **RQ1 (Safety):** Can the Safety Triage Agent detect crisis intent with high sensitivity while keeping false negatives minimal, and escalate within an acceptable time budget?
2. **RQ2 (Orchestration Correctness):** How reliably does the LangGraph orchestration execute agent reasoning loops, validate tool-call schemas, and handle transient failures through retry and fallback logic?
3. **RQ3 (Quality):** Do Support Coach responses meet a basic standard of CBT-informed guidance and appropriateness as rated by human evaluators on a small, blinded set?
4. **RQ4 (Insights, minimal):** Can the Insights Agent produce stable, aggregate-only summaries under privacy thresholds without exposing individual data?

These questions directly inform the evaluation in Chapter IV through scenario-based tests and simple, transparent metrics (e.g., sensitivity/specificity, tool-call success rate, latency percentiles, rubric scores), with human oversight preserved for safety-critical cases.

1.5 Scope and Limitations

To ensure the feasibility and focus of this bachelor's thesis, the following boundaries are explicitly established:

1. **Focus on Multi-Agent Architecture Only:** This research is focused exclusively on the **design, implementation, and evaluation of the multi-agent AI framework it-**

self—the Safety Agent Suite's BDI-based specialist agents, the Aika Meta-Agent orchestration layer, and their collective behavior in safety-critical conversational scenarios. The full UGM-AICare implementation includes database schema design, user interface components, blockchain token systems, and deployment infrastructure; however, **these system components are documented as implementation context but are not subjects of formal evaluation in this work**.

2. **Scenario-Based Evaluation, Not Clinical Trial:** The evaluation of the framework is based on **controlled, scenario-based testing** using synthetic conversational data representing maternal health crisis situations. This approach validates the technical feasibility of agent workflows and architectural integrity. It does **not** measure long-term psychological outcomes, therapeutic efficacy on real users, or operational cost savings—such claims would require extensive ethics approval, medical supervision, and longitudinal clinical studies that exceed the timeline and scope of bachelor's-level research.

3. **Simulated Data for Privacy and Feasibility:** All testing utilizes **synthetically generated crisis scenarios and simulated conversation patterns**, not real user data. This approach is necessary to protect privacy during development and to enable controlled evaluation without requiring human subjects approval. However, it means that agent performance has not been validated on the specific linguistic diversity, cultural contexts, and edge cases of a live Indonesian student population.

4. **Privacy-Aware Design Without Formal Proofs:** This research does not pursue full differential privacy proofs or cryptographic verification. Instead, it implements a practical privacy pipeline with PII redaction, UUID-based anonymization, and aggregate-only reporting thresholds to demonstrate **privacy-aware agent behavior** within the prototype context.

5. **Proof-of-Concept Scope:** The UGM-AICare platform serves as the implementation vehicle for the Safety Agent Suite, providing necessary backend services and API infrastructure. The prototype demonstrates technical feasibility and serves as a foundation for future production deployment, but is not itself a clinically validated, production-ready system for deployment with real pregnant women without further extensive validation.

1.6 Contributions

This thesis contributes a focused blueprint and evidence base for safety-oriented agentic support:

1. **Safety pipeline specification**. A concrete guideline for triage and escalation: risk cues and scoring, guardrails and redaction steps, decision thresholds, human-in-the-loop

invariants, and service targets such as time-to-escalation.

2. **Agent orchestration design**. A LangGraph view of the Safety Agent Suite—nodes, edges, and typed state schemas—plus the supporting tool-use protocol (validated schemas, idempotency, retry/backoff) that keeps workflows predictable.
3. **Evaluation assets and findings**. Scenario-based tests (synthetic crisis set, adversarial prompts, blinded coaching rubric) and their results, covering safety sensitivity, orchestration reliability, latency, and coaching quality under human oversight.

1.7 Thesis Outline

The structure of this thesis is outlined as follows:

Chapter I: Introduction. This chapter elaborates on the background of the study, the justification for the research's significance, the problem formulation to be addressed, and the specific objectives to be achieved. It also defines the scope and limitations of the research, outlines the expected contributions, and presents the overall organizational structure of the thesis report.

Chapter II: Literature Review and Theoretical Framework. This chapter surveys prior work on agentic and conversational AI for mental health, safety-critical triage systems, human-in-the-loop design, and privacy-aware analytics. It establishes the theoretical foundation that underpins the core concepts and technologies utilized in this research.

Chapter III: System Design and Architecture. This chapter outlines the methodology and technical blueprint for the system. It explains the adoption of Design Science Research and presents the system's high-level conceptual architecture, focusing on the five components of the **Safety Agent Suite**: four specialized agents (STA, SCA, SDA, IA) and the Aika Meta-Agent orchestrator. It details the underlying cloud-native technical architecture, justifying the chosen technology stack, including the use of **LangGraph** for agent orchestration and a **FastAPI** backend for the core application logic. It also describes the database structure, user interface design, and integrated security and privacy measures like differential privacy.

Chapter IV: Implementation and Evaluation. This chapter describes the development and testing of the system prototype. This chapter details the technical environment used for implementation and demonstrates the functional prototype that was built. It then explains the testing process used to evaluate the system's performance against its design requirements. The chapter concludes by presenting the results from these tests and providing an analysis of the findings.

Chapter V: Conclusion and Future Work. This chapter summarizes the study's findings and contributions. This chapter revisits the initial research problems and presents the main conclusions drawn from the research. It concludes by offering recommendations for both the future development of the system and for subsequent research in this area.

CHAPTER II
LITERATURE REVIEW AND THEORETICAL BACKGROUND

This chapter establishes the academic context for the research. It begins by surveying the existing literature on AI applications in mental health and student support to identify the limitations of current approaches. It then details the theoretical framework and enabling technologies that provide the foundation for the proposed solution. Finally, it synthesizes these areas to formally identify the research gap this thesis addresses.

2.1 Literature Review: The Landscape of AI in University Mental Health Support

This review surveys existing research at the intersection of artificial intelligence, institutional support systems, and student mental health. The aim is to contextualize the present work by examining the evolution and limitations of current approaches, thereby setting the stage for the introduction of a more advanced, agentic framework.

2.1.1 Conversational Agents for Mental Health Support

The application of conversational agents in mental health has evolved significantly, from early experiments in simulating dialogue to sophisticated, evidence-based therapeutic tools. This evolution reveals both the immense potential of these technologies and the persistent operational limitations that motivate the current research.

2.1.1.1 Evolution from Rule-Based Systems to LLM-Powered Agents

The concept of using a computer program for therapeutic dialogue dates back to Weizenbaum's ELIZA (1966), a system that used simple keyword matching and canned response templates to mimic a Rogerian psychotherapist [16, 17]. While a landmark in human-computer interaction, ELIZA and subsequent rule-based systems lacked any true semantic understanding, memory, or capacity for evidence-based intervention. Their primary limitation was their inability to move beyond superficial pattern recognition, leading to brittle and often nonsensical conversations when faced with inputs outside their predefined rules [16].

The advent of Large Language Models (LLMs) has catalyzed a paradigm shift. Modern conversational agents, powered by Transformer architectures, can generate fluent, empathetic, and context-aware responses. These models are pre-trained on vast text corpora, enabling them to understand linguistic nuance and generate human-like text. This has allowed for the development of agents that can engage in more meaningful, multi-turn conversations, moving beyond simple question-answering to provide more substantive support [17].

2.1.1.2 Therapeutic Applications and Efficacy

Contemporary mental health chatbots leverage LLMs to deliver a range of evidence-based interventions. A primary application is the delivery of psychoeducation and structured exercises from therapeutic modalities like Cognitive Behavioral Therapy (CBT). Systems such as Woebot have been the subject of randomized controlled trials (RCTs), which have demonstrated their efficacy in reducing symptoms of depression and anxiety among university students by delivering daily, brief, conversational CBT exercises [18, 19]. Other platforms, like Tess, have shown similar positive outcomes by providing on-demand emotional support and coping strategies.

These tools offer several key advantages:

- **Accessibility and Scalability:** They are available 24/7, overcoming the time and resource constraints of traditional human-led services.
- **Anonymity:** They provide a non-judgmental and anonymous space for users to disclose their feelings, which can lower the barrier for individuals who fear stigma [20].

2.1.1.3 The Dominant Reactive Paradigm and Its Limitations

Despite their technological sophistication and therapeutic potential, the fundamental operational model of these applications remains overwhelmingly **reactive and user-initiated**. They are designed as standalone tools that depend on the student to possess the self-awareness to recognize their distress, the motivation to seek help, and the knowledge of the tool's existence.

This paradigm fails to account for significant, well-documented barriers to help-seeking. Research shows that many individuals, particularly young adults, do not seek professional help for mental health issues due to factors including self-stigma, fear of judgment, and a desire for self-reliance [21, 22]. Furthermore, the very symptoms of mental health conditions, such as the anhedonia and executive dysfunction associated with depression, can severely impair an individual's ability to initiate action and seek support [23].

A systematic review of mental health chatbots for university students concluded that while these tools are promising, their primary limitation is their passive nature; they do not and cannot initiate contact or intervene based on a student's changing needs unless the student opens the app [24]. This leaves the most vulnerable studentsm, those who are not actively seeking help, unsupported, creating a critical gap in the continuum of care that this thesis aims to address.

2.1.2 Data Analytics for Proactive Student Support

Parallel to the development of conversational AI, the field of higher education has seen a rise in the use of data analytics to support student success. This section reviews the evolution of these analytical approaches, from established learning analytics to the more nascent field of well-being analytics, and identifies the key limitations that motivate the design of the agents.

2.1.2.1 Learning Analytics for Academic Intervention

The domain of **Learning Analytics** is well-established and focuses on the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [25]. Typically, these systems analyze data from institutional sources such as the Learning Management System (LMS), student information systems, and library databases. By modeling variables like assignment submission times, forum participation, and grades, institutions can build predictive models to identify students at high risk of academic failure or dropout [26]. These systems have proven effective in enabling timely academic interventions, such as targeted tutoring or advisor outreach, thereby improving student retention and success rates.

2.1.2.2 The Challenge of Well-being Analytics

More recently, researchers have attempted to extend the principles of learning analytics to the more complex and sensitive domain of student well-being. The goal is to create early-warning systems by identifying behavioral proxies for mental distress. Studies have explored the use of non-academic data sources, such as campus card usage for building access, meal plan data, and social event attendance, to find correlations with well-being outcomes [27]. For example, a sudden decrease in social activity or irregular campus attendance could be interpreted as a potential indicator of withdrawal or depression.

However, this approach is fraught with significant theoretical and practical challenges. Firstly, the "signal-to-noise" ratio is extremely low; the link between such indirect behavioral data and a student's internal mental state is often weak, correlational, and highly prone to misinterpretation [28]. A student may miss meals for many reasons other than depression. Secondly, these methods raise profound ethical questions regarding student privacy and surveillance, as they involve monitoring non-academic aspects of student life, often without explicit, ongoing consent for this specific purpose [27, 28].

A more direct, and arguably more ethical, source of data is the language students use when interacting with university services. The text from chat logs, when properly anonymized, provides a direct window into student concerns. The application of sentiment analysis and topic modeling to this textual data can yield far more reliable insights into the specific stressors affecting the student population at any given time. This approach, which is central to the design of the Analytics Agent, shifts the focus from inferring mental state from indirect behaviors to directly analyzing the expressed concerns of the student body [27].

2.1.2.3 The Insight-to-Action Gap

Whether based on academic, behavioral, or textual data, a critical limitation plagues nearly all current analytical systems in higher education: the **insight-to-action gap** [11]. The output of these systems is almost universally a dashboard, a report, or an alert delivered to a human administrator (e.g., a counselor, dean, or advisor) [12]. This administrator must then manually interpret the data, decide on an appropriate intervention strategy, and execute it.

This manual process creates a severe bottleneck that fundamentally limits the scalability, speed, and personalization of any proactive effort [29]. An administrator may be able to respond to a handful of individual alerts, but they cannot manually orchestrate a personalized outreach campaign to hundreds of students who may be exhibiting early signs of exam-related stress identified by a topic model. The manual-execution step prevents the institution from fully capitalizing on the proactive insights generated by its analytical systems. It is this specific gap that the proposed **Safety Coaching Agent** and **Safety Triage Agent** is designed to close by automating the link between data-driven insight and scalable, targeted outreach.

2.2 Theoretical Background

To address the limitations of reactive, disconnected support systems, a new architectural approach is required. This section details the theoretical framework and enabling technologies that provide the foundation for the proposed agentic AI system. These concepts are presented as the necessary components to build a proactive, integrated, and autonomous solution.

2.2.1 Foundational Principles of the Framework

Beyond the technical architecture, the proposed framework is grounded in several key strategic and ethical principles that justify its design and purpose. These concepts from service design, management science, and data ethics provide the theoretical motivation for shifting how institutional support is delivered.

2.2.1.1 Proactive vs. Reactive Support Models

The traditional approach to institutional support, particularly in mental health, is predominantly **reactive**. This model, common in service design, operates on a "break-fix" basis, where the service delivery is initiated only after a user (in this case, a student) self-identifies a problem and actively seeks a solution [30]. This places the onus of initiation entirely on the individual, creating significant barriers to access such as stigma, lack of awareness, or the inability to act during a crisis. In contrast, a **proactive support model** aims to anticipate needs and intervene before a problem escalates. Drawing from principles in preventative healthcare and proactive customer relationship management, this model uses data to identify patterns and risk factors, enabling the institution to offer timely, relevant support to at-risk cohorts [31, 32]. This thesis is an explicit attempt to architect a system that facilitates this strategic shift from a reactive to a proactive support paradigm.

Formalization of Support Models To formalize this distinction, a reactive support system operates conditionally based on user initiation:

$$\text{Support}(t) = \begin{cases} f(\text{request}_t) & \text{if student initiates} \\ \emptyset & \text{otherwise} \end{cases} \tag{2-1}$$

In contrast, a proactive system continuously monitors and responds to indicators of need:

$$\text{Support}(t) = g(\text{risk}(t), H_{t-\Delta t:t}, \text{trends}_t) \tag{2-2}$$

where $H_{t-\Delta t:t}$ represents recent interaction history and trends_t captures population-level signals from analytics.

The help-seeking barrier can be modeled as:

$$P(\text{seek help}) = f(\text{severity}) - \beta(\text{stigma}, \text{awareness}, \text{fatigue}) \tag{2-3}$$

where β captures systemic barriers such as stigma, lack of awareness, and decision fatigue. When $P(\text{seek help}) < 0$, students in crisis remain silent, justifying the need for proactive intervention that does not depend on self-initiation.

2.2.1.2 Data-Driven Decision-Making in Higher Education

The concept of **Data-Driven Decision-Making (DDDM)** posits that strategic decisions should be based on objective data analysis and interpretation rather than solely on intuition or tradition [31, 32]. In higher education, this has manifested as the field of learning analytics, where student data is used to improve learning outcomes and retention. This framework extends that principle to student well-being. The **Insights Agent** is the core enabler of DDDM for the university's support services. By autonomously processing anonymized interaction data to identify trends, sentiment shifts, and emerging topics of concern, it provides administrators with actionable, empirical evidence. This allows the institution to move beyond anecdotal evidence and allocate resources, such as workshops, counselors, or targeted information campaigns, to where they are most needed, thereby optimizing the efficiency and impact of its support ecosystem [33].

2.2.1.3 Privacy by Design (PbD)

Given the highly sensitive nature of mental health data, the framework's architecture is guided by the principles of **Privacy by Design (PbD)**. PbD is an internationally recognized framework, formalized in ISO 31700, which dictates that privacy should be the default, embedded into the design and architecture of systems from the outset rather than being an add-on feature [34,35]. Key principles include being proactive not reactive, making privacy the default setting, and providing end-to-end security. A direct implementation of PbD within this framework is the Data Anonymization Pipeline. This process ensures that Personally Identifiable Information (PII) is identified and redacted from all chat logs before they are stored for analysis. Furthermore, access to the administrative dashboard is controlled by a strict Role-Based Access Control (RBAC) mechanism, ensuring that only authorized personnel can view sensitive data. These measures, combined with standard security practices like data encryption, embed privacy and security directly into the system's architecture from the outset [33,34]. This demonstrates a commitment to building a system that is not only effective but also fundamentally ethical and secure. While this thesis focuses on the multi-agent architecture itself, these privacy-preserving design principles inform the overall framework context in which the agents operate.

2.2.2 Agentic AI and Multi-Agent Systems (MAS)

The paradigm of Artificial Intelligence (AI) has evolved significantly from systems that perform singular, reactive tasks to those that exhibit autonomous, proactive, and social behaviors. A cornerstone of this evolution is the concept of an **intelligent agent**. An agent is not merely a program; it is a persistent computational entity with a degree of autonomy, situated within an environment, which it can both perceive and upon which it can act to achieve a set of goals or design objectives [36]. The defining characteristic of an agent is its **autonomy**, its capacity to operate independently, making decisions and initiating actions without direct, constant human intervention. This is distinct from traditional objects, which are defined by their methods and attributes but do not exhibit control over their own behavior [14].

To operationalize this concept, this thesis formally introduces a framework built upon four distinct, specialized intelligent agents that form the **Safety Agent Suite**, coordinated by a unified orchestration layer. Each specialist agent is designed to address a specific challenge outlined in Chapter 1, while the orchestrator ensures seamless, role-appropriate interactions. Together they form the core of the proposed proactive support system. The framework components are:

- The **Safety Triage Agent (STA)**, responsible for real-time risk assessment and crisis intervention.
- The **Support Coach Agent (SCA)**, responsible for delivering personalized, evidence-based coaching.
- The **Service Desk Agent (SDA)**, responsible for managing clinical case workflows and administrative tasks.
- The **Insights Agent (IA)**, responsible for privacy-preserving data analysis and trend identification.
- The **Aika Meta-Agent**, responsible for context-aware routing, role-based access control, and synthesizing coherent responses across specialist agents.

The theoretical underpinnings of these agents' architecture and behavior are drawn from established models of rational agency and multi-agent systems, as detailed below.

Fundamentally, an agent's operation is defined by a continuous cycle of perception, reasoning (or deliberation), and action. It perceives its environment through virtual **sensors** (e.g., data feeds, API calls, database queries) and influences that environment through its **actuators** (e.g., sending emails, generating reports, invoking other services) [37]. A prominent and highly relevant architecture for designing such goal- oriented agents is the **Belief-Desire-Intention (BDI)** model [37,38]. This model provides a framework for rational agency that mirrors human practical reasoning:

- **Beliefs:** This represents the informational state of the agent, its knowledge about the environment, which may be incomplete or incorrect. For the **Insights Agent**, beliefs correspond to the current understanding of student well-being trends derived from anonymized data.
- **Desires:** These are the motivational states of the agent, representing the objectives or goals it is designed to achieve. Desires can be seen as the potential tasks the agent could undertake, such as the **Support Coach Agent's** overarching goal to "deliver personalized coaching."
- **Intentions:** This represents the agent's commitment to a specific plan or course of action. An intention is a desire that the agent has chosen to actively pursue. For instance, the **Safety Triage Agent**, upon identifying a high-severity conversation, forms

an intention to immediately route the user to emergency resources.

The BDI framework allows for the design of agents that are not merely reactive but are proactive and deliberative, capable of reasoning about how to best achieve their goals given their current beliefs about the world [14, 38].

To formally ground the proposed framework in this established model, the roles and logic of each of the five framework components (four specialist agents plus the orchestrating meta-agent) are mapped to the BDI components in Table 2.1. This mapping clarifies how each component perceives its environment, formulates its objectives, and decides on a concrete course of action, allowing for the design of agents that are not merely reactive but are proactive and deliberative, capable of reasoning about how to best achieve their goals given their current beliefs about the world.

Formalization of the BDI Cycle The BDI model operates through continuous state updates that govern how agents perceive, deliberate, and act. The cycle can be formalized as:

Belief Update: An agent's beliefs are updated as new information is perceived:

$$Bel_{t+1} = Bel_t \cup \{\text{percept}_t\} \setminus \{\text{expired beliefs}\} \tag{2-4}$$

where percept_t represents new observations from the environment, and expired beliefs are those that are no longer valid or relevant.

Desire Selection: The agent filters potential goals based on its current beliefs:

$$Des_t = \text{filter}(\text{Options}_t, Bel_t) \tag{2-5}$$

where Options_t represents all possible goals the agent could pursue, and the filter function selects those that are feasible given current beliefs.

Intention Formation: The agent commits to a specific plan of action through deliberation:

$$Int_t = \text{deliberate}(Des_t, Bel_t, Int_{t-1}) \tag{2-6}$$

where the deliberation process considers current desires, beliefs, and previous intentions to form a committed plan.

For example, in the **Safety Triage Agent (STA)**, percept_t is the incoming student message M_t, beliefs include prior conversation context and crisis patterns, desires map to intervention goals (de-escalation, resource connection), and intentions become the selected action (escalate to SDA, provide coping strategy, or direct to emergency resources).

Table 2.1. Mapping of the Agentic Framework to the BDI Model.

Agent	**Beliefs** *(Informational State)*	**Desires** *(Motivational Goals)*	**Intentions** *(Committed Plans)*
STA	• User's conversation history • Severity classification model • Emergency resources directory	• Assess immediate risk level • Provide appropriate support	• Escalate high-severity cases • Display emergency contacts
SCA	• User goals & history • Evidence-based intervention library (CBT)	• Deliver personalized coaching • Guide through exercises	• Deliver specific CBT exercise • Provide empathetic responses
SDA	• Clinical case status • Counselor availability • User appointment requests	• Manage case workflows • Schedule appointments	• Find available appointment slots • Create and update case notes
IA	• Anonymized conversation database • Last report timestamp • Known topic models	• Identify emerging trends • Quantify sentiment shifts	• Generate weekly summary reports • Execute database queries
Aika Meta-Agent	• User role and authentication context (student/counselor/admin). • Conversation history and session state across all agents. • Routing policies and agent capability mappings. • Current risk assessment from STA (if applicable).	• To provide a unified, role-appropriate interface for all users. • To ensure safety-first routing for all student interactions. • To coordinate multi-agent workflows seamlessly.	• Upon receiving a user message, form an intention to classify intent and route to appropriate specialist(s). • To synthesize specialist responses with role-consistent personality. • To maintain conversational coherence across agent transitions.

When multiple agents, each with its own goals and capabilities, co-exist and interact within a shared environment, they form a **Multi-Agent System (MAS)**. An MAS is a system in which the overall intelligent behavior and functionality are a product of the collective, emergent dynamics of its constituent agents [39, 40]. The power of an MAS lies in its ability to solve problems that would be difficult or impossible for a monolithic system or a single agent to handle. This is achieved through social interaction, primarily:

- **Coordination and Cooperation:** Agents must coordinate their actions to avoid interference and cooperate to achieve common goals. In this thesis, the **Insights**, **Support Coach**, **Safety Triage**, and **Service Desk** agents must cooperate: the Insights Agent provides the data-driven insights (beliefs) that the Support Coach Agent uses to form its outreach plans (intentions), while the Safety Triage Agent handles immediate, real-time needs that may fall outside the other agents' scopes, and the Service Desk Agent manages the administrative follow-up.
- **Negotiation:** When agents have conflicting goals or must compete for limited resources, they must be able to negotiate to find a mutually acceptable compromise [41, 42].
- **Communication:** Effective interaction requires a shared Agent Communication Language (ACL), such as FIPA-ACL or KQML, which defines the syntax and semantics for messages, allowing agents to perform actions like requesting information, making proposals, and accepting or rejecting tasks [43, 44].

Therefore, this thesis leverages the MAS paradigm by designing a framework composed of four specialized, collaborative agents coordinated by a meta-agent orchestrator. Their individual, goal-directed behaviors, orchestrated within a hierarchical architecture, work in concert to achieve the overarching systemic objective: transforming institutional mental health support from a reactive model to a proactive, data-driven ecosystem.

2.2.2.1 Mathematical Formalization of Agent Decision Functions

To operationalize the BDI model for the Safety Agent Suite, each agent's core decision-making process is formalized as a mathematical function mapping inputs to outputs. This formalization bridges the theoretical BDI framework to the practical implementation described in Chapter 3.

Safety Triage Agent (STA) The STA assesses risk level $R_t \in \{0, 1, 2, 3\}$ from student message M_t:

$$R_t = f_{STA}(M_t; \theta_{LLM}, \mathcal{C}) \tag{2-7}$$

where θ_{LLM} represents the LLM parameters (Gemini 2.5 Flash) and $\mathcal{C}$ is the crisis pattern corpus used for contextual understanding. The discrete risk level maps to severity categories:

$$\text{severity}(R_t) = \begin{cases} \text{low} & R_t = 0 \\ \text{moderate} & R_t = 1 \\ \text{high} & R_t = 2 \\ \text{critical} & R_t = 3 \end{cases} \tag{2-8}$$

This classification determines subsequent routing: moderate risk ($R_t = 1$) triggers supportive coaching via SCA, while high or critical risk ($R_t \geq 2$) initiates immediate escalation to the Service Desk Agent for clinical case management.

Support Coach Agent (SCA) The SCA generates therapeutic response A_t given the current message and conversation history:

$$A_t = f_{SCA}(M_t, H_{t-1}; \theta_{LLM}, \mathcal{I}) \tag{2-9}$$

where $H_{t-1} = \{(M_0, A_0), \ldots, (M_{t-1}, A_{t-1})\}$ is the conversation history capturing previous exchanges, and $\mathcal{I}$ represents the intervention library containing evidence-based therapeutic frameworks (CBT, Motivational Interviewing). The history dependency enables the agent to maintain therapeutic continuity and adapt interventions based on student progress.

Insights Agent (IA) The IA computes aggregate metric μ from anonymized message set $\mathcal{M}$:

$$\mu = f_{IA}(\mathcal{M}, q; \mathcal{K}) \tag{2-10}$$

where q represents the analytical query (e.g., crisis trend analysis, topic modeling, sentiment aggregation) and $\mathcal{K}$ enforces privacy constraints such as k-anonymity and query result suppression. The IA's output informs institutional decision-making by quantifying population-level trends while preserving individual privacy.

Service Desk Agent (SDA) The SDA determines administrative action α_t based on case state and available resources:

$$\alpha_t = f_{SDA}(C_t, R_{avail}; \theta_{LLM}) \tag{2-11}$$

where C_t represents the current case state (severity, student information, appointment history) and R_{avail} denotes available resources (counselor schedules, emergency contact protocols). Actions include appointment scheduling, case note creation, and resource allocation.

These formalizations establish the mathematical foundation for the multi-agent coordination described in subsequent sections and implemented in Chapter 3.

2.2.3 Large Language Models (LLMs)

Large Language Models (LLMs) are a class of deep learning models that have demonstrated remarkable capabilities in understanding and generating human-like text. The architectural foundation for virtually all modern LLMs, including the Gemini models used in this research, is the **Transformer architecture**, first introduced by Vaswani et al. [45]. The Transformer's key innovation is the **self-attention mechanism**, which allows the model to dynamically weigh the importance of different words in an input sequence when processing and generating language. This enables the model to capture complex, long-range dependencies and contextual relationships far more effectively than its predecessors, such as Recurrent Neural Networks (RNNs) [46, 47].

The Self-Attention Mechanism The self-attention mechanism computes contextual representations by relating different positions in a sequence to each other. Given an input sequence, the mechanism computes three matrices: Query (Q), Key (K), and Value (V), each derived through learned linear projections of the input embeddings. The attention operation is then defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2-12}$$

where d_k is the dimension of the key vectors. The scaling factor $\sqrt{d_k}$ prevents the dot products from growing too large, which would push the softmax function into regions with extremely small gradients.

The attention weights, computed by the softmax of the scaled dot products between queries and keys, determine how much each position in the sequence should attend to every other position. These weights are then used to compute a weighted sum of the value vectors, producing contextually-aware representations.

Modern Transformers employ **multi-head attention**, which applies multiple attention operations in parallel, each with different learned projections:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \tag{2-13}$$

where $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$ and W^O is an output projection matrix. This allows the model to attend to information from different representation subspaces simultaneously. For instance, Gemini 2.5 employs 32 attention heads per layer, enabling it to capture diverse linguistic patterns and semantic relationships concurrently.

The core operation of a Transformer-based model involves processing input text through a series of encoding and/or decoding layers. The process can be conceptualized as follows:

1. **Tokenization and Embedding:** Input text is first broken down into smaller units called tokens. Each token is then mapped to a high-dimensional vector, or an "embedding," that represents its semantic meaning.
2. **Positional Encoding:** Since the self-attention mechanism does not inherently process sequential order, a positional encoding vector is added to each token embedding to provide the model with information about the word's position in the sequence.
3. **Self-Attention Layers:** The sequence of embeddings passes through multiple self-attention layers. In each layer, the model calculates attention scores for every token relative to all other tokens in the sequence, effectively learning which parts of the input are most relevant for understanding the context of each specific token.
4. **Feed-Forward Networks:** Each attention layer is followed by a feed-forward neural network that applies further transformations to each token's representation.
5. **Output Generation:** The model's final output is a probability distribution over its entire vocabulary for the next token in the sequence. The model then typically selects the most likely token (or samples from the distribution) and appends it to the input, repeating the process autoregressively to generate coherent text [46].

This research utilizes a cloud-based API model strategy, leveraging the Gemini 2.5 family of models to balance performance, privacy, and capability. The Gemini models represent Google's state-of-the-art, natively multimodal foundation models, available in various sizes (e.g., Gemini Pro). Unlike models trained solely on text, Gemini was pre-trained from the ground up on multiple data modalities, giving it more sophisticated reasoning capabilities [48]. In this framework, a powerful model like Gemini 2.5 Pro is accessed via a secure API for all agentic tasks [49], from the real-time conversation handling of the Safety Triage Agent to the complex, non-sensitive tasks, such as the weekly trend analysis performed by the Insights Agent.

2.2.3.1 Cloud-Based API Models: The Gemini 2.5 Family

The framework integrates a state-of-the-art, proprietary model accessed via a cloud API. The Gemini family, specifically the flagship **Gemini 2.5 Flash** model, serves this role, providing a level of reasoning and multimodal understanding that is critical for handling the most complex tasks and ensuring system robustness. While a detailed architectural schematic is not public, in line with the proprietary nature of frontier AI models,

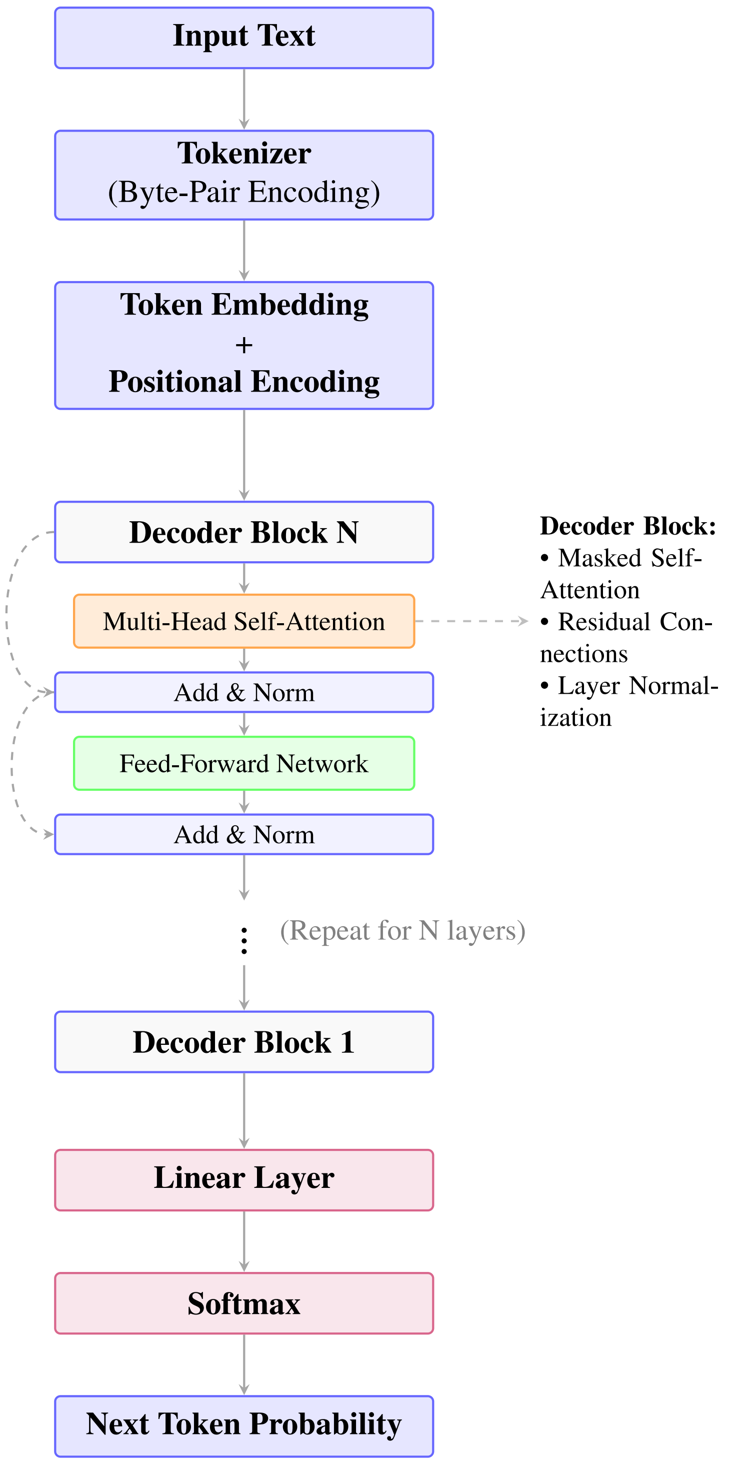


Figure 2.1. A simplified view of the decoder-only Transformer architecture used in generative LLMs. The model processes input embeddings through multiple layers (blocks) of masked multi-head self-attention and feed-forward networks with residual connections to predict the next token in a sequence.

its capabilities have been extensively documented by Google through official developer guides and announcements [48, 49].

Gemini 2.5 builds upon the efficient **Mixture-of-Experts (MoE) Transformer** architecture of its predecessors. In an MoE architecture, the model is composed of numerous smaller "expert" neural networks. For any given input, a routing mechanism activates only a sparse subset of these experts. This allows the model to have a very large total parameter count, enabling vast knowledge and capability, while keeping the computational cost for any single inference relatively low [48].

The strategic role of Gemini 2.5 in this framework is defined by its next-generation capabilities:

- **Native Multimodality with Expressive Audio:** A significant architectural leap in Gemini 2.5 is its native handling of audio [50]. Unlike models that first transcribe audio to text, Gemini 2.5 processes audio streams directly. This allows it to understand not just the words, but also the nuances of human speech such as tone, pitch, and prosody, which is invaluable for a mental health application where user sentiment is key.
- **Controllable Reasoning and "Thinking Time":** Gemini 2.5 introduces a "thinking budget," a mechanism that allows developers to control the trade-off between response latency and reasoning depth [48]. For high-frequency tasks performed by the Safety Triage Agent, a lower budget can ensure speed. For complex analytical tasks required by the Insights Agent, a higher budget can be allocated to allow for more thorough reasoning, providing granular control over both cost and quality.
- **Advanced Agentic Capabilities and Tool Use:** The model is explicitly designed to power advanced agents. It features more reliable and sophisticated function calling, enabling seamless integration with external tools and APIs [48]. This is essential for the Service Desk Agent to execute multi-step plans, such as scheduling an appointment based on a user's request.
- **High-Fidelity Reasoning:** As a frontier model, Gemini 2.5 serves as the high-capability engine for all requests, ensuring service continuity and the highest quality output.

By integrating Gemini 2.5 via its API, the agentic framework gains access to state-of-the-art reasoning power on demand, ensuring that it can handle a wide spectrum of tasks with both efficiency and exceptional quality.

2.2.4 LLM Orchestration Frameworks

While LLMs provide powerful reasoning capabilities, they are inherently stateless and lack direct access to external data or tools. An LLM, in isolation, cannot query a database, call an API, or access a private document. To build sophisticated, stateful applications that overcome these limitations, an orchestration framework is required.

2.2.4.1 LangChain: The Building Blocks of LLM Applications

LangChain is an open-source framework designed specifically for this purpose, providing the essential "glue" to connect LLMs with external resources and compose them into complex applications [51, 52]. The core philosophy of LangChain is to provide modular components that can be "chained" together to create complex workflows. The most recent and fundamental abstraction in LangChain is the **LangChain Expression Language (LCEL)**. LCEL provides a declarative, composable syntax for building chains, where the pipe (‘|‘) operator streams the output of one component into the input of the next. Every component in an LCEL chain is a "Runnable," a standardized interface that supports synchronous, asynchronous, batch, and streaming invocations, making it highly versatile for production environments [52, 53].

A simple LCEL chain can be represented as:

$$\text{Chain} = \text{PromptTemplate} \mid \text{LLM} \mid \text{OutputParser}$$

In this sequence, user input is first formatted by a ‘PromptTemplate‘, the result is passed to the ‘LLM‘ for processing, and the LLM’s raw output is then transformed into a structured format (e.g., JSON) by an ‘OutputParser‘.

For this thesis, the most critical application of LangChain is its ability to create **agents**. A LangChain agent uses an LLM not just for text processing, but as a reasoning engine to make decisions. This is often based on a framework known as **ReAct (Reasoning and Acting)**, which enables the LLM to synergize reasoning and action [51, 54]. The agent is given access to a set of **Tools**, which are simply functions that can interact with the outside world (e.g., a database query function, a file reader, a web search API). The agent’s operational loop, managed by an **Agent Executor**, can be formalized as an iterative process.

Let G be the initial goal and H_t be the history of actions and observations up to step t. The process at each step t is:

1. **Reasoning (Thought Generation):** The agent generates a thought th_t and a subsequent action a_t by sampling from the LLM’s conditional probability distribution, given the goal and the history so far.

   $$(th_t, a_t) \sim p(th, a | G, H_{t-1}; \theta_{LLM})$$

   The prompt to the LLM contains the goal and the trajectory of previous thoughts, actions, and observations, guiding its next decision.

2. **Action Execution:** The Agent Executor parses a_t to identify the chosen tool and its input, then executes it to produce an observation, o_t.

$$o_t = \text{ExecuteTool}(a_t)$$

3. **History Augmentation:** The new observation is appended to the history, forming the context for the next iteration.

$$H_t = H_{t-1} \oplus (a_t, o_t)$$

   This loop continues until the LLM determines the goal G is met and generates a final answer.

This iterative loop is what transforms a passive LLM into a proactive, problem-solving agent. For example, the **Insights Agent** in this framework, when tasked with "summarizing student stress trends," would use this loop to formulate a SQL query (Thought and Action), execute it (Observation), and then use the results to generate a final summary. This orchestration is fundamental to enabling the autonomous capabilities central to this thesis.

2.2.4.2 LangGraph: Orchestrating Multi-Agent Systems

While LangChain's standard agent executors are powerful, they are often designed for linear, sequential execution paths. For a sophisticated multi-agent system like the **Safety Agent Suite**, where agents must collaborate, hand off tasks, and operate in a cyclical, stateful manner, a more robust orchestration mechanism is required. This is the role of **LangGraph**, an extension of LangChain designed for building durable, stateful, multi-agent applications by modeling them as cyclical graphs [55, 56].

The core concept of LangGraph is to represent the agentic workflow as a **state graph**. This is a directed graph where nodes represent functions or LLM calls (the "work" to be done) and edges represent the conditional logic that directs the flow of execution from one node to another. A central **State** object is passed between nodes, allowing each agent or tool to read the current state, perform its function, and then update the state with its results. This creates a persistent, auditable record of the agent's operations [53, 57].

A LangGraph workflow can be defined by the following components:

- **State Graph:** The overall structure, $G = (N, E)$, where N is a set of nodes and E is a set of directed edges. The graph's state is explicitly defined by a state object that is passed and updated throughout the execution.
- **Nodes:** Each node represents an agent or a tool. When called, a node receives the current state object as input and returns a dictionary of updates to be applied to the

state. For example, the ‘Safety Triage Agent‘ node would take the user’s message from the state, process it, and return an update specifying the assessed risk level.

- **Edges:** Edges connect the nodes and control the flow of the application. LangGraph supports **conditional edges**, which are crucial for agentic behavior. After a node executes, a routing function is called to inspect the current state and decide which node to move to next [52,53]. For example, after the ‘Safety Triage Agent‘ runs, a conditional edge might route the workflow to the ‘Service Desk Agent‘ if the risk is moderate, or directly to an "escalate" tool if the risk is critical.

State Transition Semantics The stateful execution of a LangGraph workflow is governed by formal state update rules. Each node in the graph transforms the shared state through a state update function:

$$S_{t+1} = \text{node}_i(S_t) = S_t \oplus \Delta S_i \tag{2-14}$$

where S_t represents the current state at time step t, ΔS_i is the update produced by node i, and $\oplus$ denotes the state merging operation (where new fields override existing values while preserving unmodified fields).

Conditional edges implement routing logic via predicate functions that inspect the current state. For the Safety Agent Suite, the routing after risk assessment can be formalized as:

$$\text{next}(S_t) = \begin{cases} \text{escalate\_to\_sda} & \text{if } S_t.\text{risk\_level} \geq 2 \\ \text{provide\_coaching} & \text{if } S_t.\text{risk\_level} = 1 \\ \text{END} & \text{if } S_t.\text{risk\_level} = 0 \end{cases} \tag{2-15}$$

This formalization enables dynamic multi-agent orchestration where the STA’s risk assessment (R_t) determines subsequent workflow paths: moderate risk routes to the SCA for therapeutic intervention, high or critical risk escalates to the SDA for clinical case creation, and low risk concludes the interaction. The explicit state management ensures that all downstream agents have access to the complete conversation context, enabling informed decision-making throughout the workflow.

More generally, for any conditional routing decision, the next node is determined by a routing function ρ:

$$\text{next\_node} = \rho(S_t) \in N \cup \{\text{END}\} \tag{2-16}$$

where ρ maps the current state to either another node in the graph or a terminal state, enabling arbitrary workflow complexity including loops, parallel execution, and human-in-the-loop interventions.

This cyclical, stateful approach provides several key advantages for this framework:

1. **Explicit Multi-Agent Collaboration:** LangGraph allows for the explicit definition of workflows where different agents are called in sequence or in parallel, and their outputs are used to inform the next step [57, 58]. This is essential for the **Safety Agent Suite**, where the ‘Insights Agent‘’s output must trigger the ‘Support Coach Agent‘.
2. **State Management and Durability:** Because the state is explicitly managed, the agent's "memory" of the conversation and its previous actions is robust. The graph's execution can be paused, resumed, and inspected, which is vital for long-running, interactive coaching sessions.
3. **Flexibility and Control:** Unlike the more constrained loops of standard agent executors, LangGraph allows for the creation of arbitrary cycles. An agent can loop, retry a tool call if it fails, or route to a human-in-the-loop for verification, providing a much higher degree of control and reliability for a safety-critical application [59,60].

By using LangGraph to orchestrate the **Safety Agent Suite**, this framework moves beyond simple, linear agentic loops and implements a true multi-agent system capable of complex, stateful, and collaborative problem-solving [55, 58].

2.2.4.3 Real-Time Performance Requirements for Safety-Critical Applications

For mental health support systems, response latency directly impacts user experience and, critically, the effectiveness of crisis intervention. To formalize these requirements, Service Level Objectives (SLOs) define the maximum acceptable latency for each agent operation.

Let T_{agent} denote the response time random variable for an agent. The p95 SLO (95th percentile) ensures that 95% of requests are handled within the target latency:

$$\Pr[T_{agent} \leq T_{target}] \geq 0.95 \tag{2-17}$$

Agent-Specific Latency Targets Different agents have different latency requirements based on their role:

Safety Triage Agent (STA): As the first-line crisis detection system, the STA requires near-instantaneous response:

$$T_{STA} \leq 250\text{ms} \quad (p95) \tag{2-18}$$

This target ensures crisis indicators are identified within human perceptual thresholds, enabling immediate escalation when necessary.

End-to-End User Experience: The complete interaction flow from user message to final response must maintain acceptable responsiveness:

$$T_{E2E} = T_{STA} + T_{routing} + T_{SCA} + T_{network} \leq 1500\text{ms} \quad (p95) \tag{2-19}$$

where $T_{routing}$ represents orchestration overhead, T_{SCA} is the Support Coach Agent's response generation time, and $T_{network}$ accounts for transmission delays.

Performance Monitoring and Alerting Node-level latency is continuously monitored through execution tracking:

$$T_{node}(i) = t_{complete}(i) - t_{start}(i) \tag{2-20}$$

where $t_{start}(i)$ and $t_{complete}(i)$ are timestamps for node initiation and completion, respectively.

Critical alerts are triggered when latency exceeds threshold values:

$$\text{alert}(i) = \begin{cases} \text{WARNING} & \text{if } T_{node}(i) > \theta_{warning} \\ \text{CRITICAL} & \text{if } T_{node}(i) > \theta_{critical} \end{cases} \tag{2-21}$$

where typical thresholds are $\theta_{warning} = 30$s and $\theta_{critical} = 2$min for backend operations.

Capacity Planning The system must maintain performance under load. Throughput requirements specify the range of concurrent sessions the system must handle:

$$\lambda_{concurrent} \in [500, 1000] \text{ sessions} \tag{2-22}$$

This capacity ensures the system scales to institutional needs while maintaining the latency targets defined above. Capacity testing validates these requirements through simulated load scenarios, as detailed in Chapter 3.

2.3 Synthesis and Identification of the Research Gap

The preceding review of the literature and theoretical landscape reveals a critical disconnect. On one hand, the field has produced increasingly sophisticated but fundamentally **reactive** conversational agents for mental health. On the other, it has developed proactive institutional analytics that remain bottlenecked by a reliance on **manual intervention**. The failure of the existing literature is not in the individual components, but in the lack of integration between them.

This creates a significant and unaddressed research gap: the need for an **integrated, autonomous, and proactive framework** that can systemically bridge the chasm from data-driven insight to automated, personalized intervention and administrative action. Current systems are not designed as a cohesive ecosystem. The analytical tools do not automatically trigger the intervention tools, the conversational agents do not seamlessly hand off tasks to administrative agents, and the user-facing support does not operate with an awareness of the broader institutional context provided by analytics.

The central argument of this thesis is that the next frontier in institutional mental health support lies not in the incremental improvement of any single component, but in the **synergistic integration of multiple specialized agents** into a single, closed-loop system. Such a system, architected as a Multi-Agent System (MAS), is capable of emergent behaviors that are more than the sum of its parts.

Therefore, this research directly addresses the identified gap by proposing and prototyping a novel agentic AI framework, the **Safety Agent Suite**, where:

- An **Insights Agent (IA)** autonomously identifies trends, moving beyond the static dashboards of current well-being analytics and creating actionable intelligence.
- A **Support Coach Agent (SCA)** and a **Safety Triage Agent (STA)** act on this intelligence and on real-time user needs, providing both proactive, personalized coaching and immediate, context-aware crisis support. They function as the intelligent front-door to the support ecosystem, overcoming the limitations of purely reactive chatbots.
- A **Service Desk Agent (SDA)** closes the "insight-to-action" loop on an administrative level, automating the workflows for clinical case management and resource allocation that currently render proactive models inefficient and unscalable.

By designing and evaluating a system where these agents work in concert, orchestrated by LangGraph, this thesis pioneers a holistic solution that is fundamentally more proactive, scalable, and efficient than the disparate tools described in the current literature.

CHAPTER III
SYSTEM DESIGN AND ARCHITECTURE

3.1 Research Methodology: Design Science Research (DSR)

The research presented in this thesis is constructive in nature, aimed not merely at describing or explaining a phenomenon, but at creating a novel and useful artifact to solve a real-world problem. To provide a rigorous and systematic structure for this endeavor, this study adopts the **Design Science Research (DSR)** methodology. DSR is a well-established paradigm in Information Systems research focused on the creation and evaluation of innovative IT artifacts intended to solve identified organizational problems [61]. The primary goal of DSR is to generate prescriptive design knowledge through the building and evaluation of these artifacts.

3.1.1 Rationale for Design Science Research

The selection of DSR as the methodological framework for this research is justified by several key considerations that align with the nature of the problem and the objectives of this study. Table 3.1 summarizes the primary justifications for adopting DSR over alternative research methodologies.

These justifications collectively establish DSR as the most appropriate methodological framework for this research, balancing the need for rigorous academic inquiry with the practical imperative of delivering a functional artifact that addresses a real-world problem.

3.1.2 The DSR Process Model

The DSR process model, as outlined by Peffers et al., provides an iterative framework that guides the research from problem identification to the communication of results [62]. This thesis follows these stages, mapping them directly to its structure to ensure a logical and transparent research process:

1. **Problem Identification and Motivation:** This initial stage, which involves defining the specific research problem and justifying the value of a solution, is addressed in **Chapter I** of this thesis. We have identified the inefficiencies of the reactive mental health support model as the core problem.
2. **Define Objectives and Knowledge Base:** Building on the identified problem, this stage formalizes the solution objectives and anchors them in the relevant knowledge base. The initial objectives are articulated in **Chapter I**, and they are refined and theoretically grounded through the literature synthesis in **Chapter 2.1**.

Table 3.1. Justifications for adopting Design Science Research methodology.

DSR Characteristic	Relevance to This Research	Contrast with Alternative Methodologies
Artifact-centric problem solving	The core contribution is the Safety Agent Suite framework itself—a novel multi-agent system architecture. DSR provides the appropriate epistemological stance for research where the primary output is a designed artifact [61].	Descriptive research methodologies focus on understanding phenomena; purely experimental approaches test hypotheses in controlled settings but do not emphasize artifact creation as the primary contribution.
Practical relevance and real-world impact	The reactive mental health support problem identified in Chapter I is a genuine organizational challenge in Higher Education Institutions worldwide. DSR bridges academic rigor and practical utility by requiring artifacts address real problems [62].	A purely theoretical approach fails to deliver actionable solutions; a purely engineering approach lacks systematic evaluation rigor. DSR offers a middle ground ensuring both practical applicability and scholarly rigor.
Iterative development and refinement	The DSR process explicitly incorporates feedback loops between design, demonstration, and evaluation stages, aligning naturally with agentic AI development where agent behaviors must be iteratively refined based on testing results.	Waterfall-style experimental research and ethnographic studies do not accommodate this iterative, build-evaluate-refine cycle as seamlessly. The cyclic nature of DSR is essential for complex system development.
Compatibility with evaluation constraints	DSR accommodates scenario-based evaluation using synthetic or controlled test cases—essential when working with sensitive mental health data where live human trials require extensive ethical approvals and pose potential risks. Detailed in Chapter IV.	Traditional empirical methodologies typically require access to real subjects and naturalistic data, which are infeasible given ethical constraints and undergraduate thesis scope.
Knowledge contribution through design	DSR explicitly recognizes that designing, building, and evaluating artifacts generates generalizable design knowledge beyond specific instantiation [61]. This thesis contributes design principles, architectural patterns (dual-loop proactive-reactive model), and evaluation criteria.	Alternative methodologies may produce case-specific findings without explicit mechanisms for abstracting generalizable design knowledge applicable to future systems in the same problem domain.

3. **Design and Development:** This is the core constructive phase where the artifact's architecture and functionalities are developed. This stage is the primary focus of the present chapter, **Chapter III**, which outlines the functional and technical blueprint of the agentic AI framework.
4. **Demonstration:** In this stage, the designed artifact is demonstrated to solve representative instances of the problem. The functional prototype and its scenario walk-throughs are presented in **Chapter IV**, particularly Sections 4.1 and 4.3.
5. **Evaluation:** This stage observes and measures how well the artifact supports the solution objectives. The scenario-based tests and their analysis are reported in **Chapter IV**, Sections 4.3–4.7.
6. **Communication of Results:** The final stage disseminates the artifact, findings, and implications to the target audience. This thesis (culminating in **Chapter V** and supported by the appendices) serves as the primary communication vehicle.

Stages 4-6 therefore operationalize the empirical programme for the research questions defined in Chapter 1.4. The demonstration assets in Chapter IV (Sections 4.1 and 4.3) instantiate the scenarios for RQ1–RQ4, while the evaluation stage reports the quantitative indicators detailed in Chapter IV: STA sensitivity/specificity for safety (RQ1), orchestration reliability metrics such as tool-call success and latency for resilience (RQ2), rubric-based CBT quality scores for coaching (RQ3), and stability of aggregate analytics for the Insights Agent (RQ4). The communication stage synthesizes these findings in Chapter V so that institutional stakeholders can interpret the metrics and translate them into policy and operational decisions. Together, the paragraph-level traceability between stages and metrics makes the DSR cycle a roadmap for the scenario-based evaluation that follows.

3.1.3 Evaluation Strategy and Data Generation Approach

Given the sensitive nature of mental health support and the ethical constraints inherent in this domain, this research adopts a scenario-based evaluation methodology using carefully designed synthetic test cases rather than live human trials. This section presents the methodological decisions governing data generation, metric selection, and instrumentation.

3.1.3.1 Rationale for Synthetic Data

The decision to employ synthetic test data rather than authentic student conversations is driven by ethical, practical, and methodological considerations. Table 3.2 summarizes the primary justifications for this approach.

This approach aligns with established practices in safety-critical AI system eval-

Table 3.2. Rationale for synthetic data in evaluation.

Consideration	**Constraint with Real Data**	**Advantage of Synthetic Data**
Ethical approval	Collecting genuine mental health crisis conversations from students requires extensive ethical review board (ERB) approval, informed consent processes, and participant safeguarding mechanisms beyond the scope of an undergraduate thesis.	Eliminates need for ERB approval as no human participants are involved; allows research to proceed within feasible timeline.
Privacy and safety risks	Even anonymized mental health disclosures carry re-identification risks and potential psychological harm to participants if data is breached or mishandled.	Removes risk of harm to real individuals; no sensitive personal data is collected or stored.
Systematic coverage	Real conversational data is opportunistic and may not include rare but critical crisis scenarios (e.g., explicit self-harm statements, acute distress patterns).	Enables controlled, systematic testing of edge cases and boundary conditions essential for safety validation [**?**].
Reproducibility	Access to real student data is typically restricted and cannot be shared for replication purposes.	Synthetic datasets can be documented, versioned, and shared with evaluators, enhancing reproducibility and transparency.

uation, where controlled test scenarios provide more comprehensive coverage than naturalistic data collection, particularly when evaluating rare high-stakes events [**?**].

3.1.3.2 Test Corpus Design

The evaluation employs three carefully constructed test datasets, each designed to exercise specific agent functionalities and stress-test system boundaries. Table 3.3 details the composition and purpose of each corpus.

Table 3.3. Test corpus design and coverage.

Corpus	**Size**	**Content Coverage**	**Primary Evaluation Target**
Crisis detection corpus	500 labeled prompts	Self-harm ideation, violence indicators, acute distress scenarios, plus emotionally charged non-crisis messages (to test specificity).	Safety Triage Agent (STA): sensitivity, specificity, false positive/negative rates.
Coaching dialogue corpus	120 conversation snippets	Common student concerns (exam stress, social isolation, relationship difficulties, sleep issues, motivation).	Support Coach Agent (SCA): response quality, empathy, CBT alignment, engagement.
Synthetic operational logs	12 weeks of simulated activity	Multi-user interaction patterns, temporal trends, cohort-level sentiment and topic distributions.	Insights Agent (IA): analytics stability, trend detection, aggregation correctness.

These datasets systematically exercise each agent's intended functionality and provide controlled conditions for measuring performance against pre-defined acceptance criteria.

3.1.3.3 Metric Selection Principles

Evaluation metrics are selected according to three guiding principles to ensure methodological rigor and practical relevance:

1. **Alignment with research questions and safety objectives:** Each metric directly addresses a specific research question or system requirement, ensuring that evaluation outcomes inform the research goals.
2. **Measurability through automated instrumentation:** Metrics must be objectively quantifiable through automated data collection to minimize measurement bias and enable continuous monitoring.

3. **Interpretability for institutional stakeholders:** Metrics are selected for their clarity and relevance to non-technical decision-makers (e.g., counseling administrators) who will assess system suitability for deployment.

Each research question maps to specific quantitative metrics with pre-defined acceptance thresholds derived from system requirements and relevant literature. The complete evaluation plan, including metric definitions and acceptance criteria, is detailed in Chapter IV, Table 4.1.

3.1.3.4 Instrumentation and Reproducibility

To ensure evaluation reproducibility and enable multi-level behavioral analysis, the prototype implements comprehensive instrumentation. Table 3.4 summarizes the instrumentation strategy.

Table 3.4. Instrumentation strategy for evaluation reproducibility.

Instrumentation Type	**Implementation**	**Purpose**
Distributed tracing	OpenTelemetry spans across all agent operations, capturing request-response latency, tool invocation timing, and inter-agent handoffs.	Enables latency analysis, bottleneck identification, and performance optimization; supports evaluation of RQ2 (orchestration reliability).
Structured logging	All agent interactions, state transitions, and decision points logged in JSON format with ISO-8601 timestamps and correlation IDs.	Facilitates replay of evaluation scenarios, supports auditing, and enables post-hoc analysis of agent reasoning chains.
Metric exporters	Prometheus exporters expose real-time counters (tool call success/failure, classification outcomes) and histograms (latency distributions).	Provides quantitative data for evaluation dashboards; enables statistical analysis of agent performance.

This multi-layered instrumentation ensures that evaluation results are reproducible, that system behaviors can be analyzed at multiple levels of granularity, and that performance data is available for both real-time monitoring and retrospective analysis.

3.1.4 Validity and Limitations

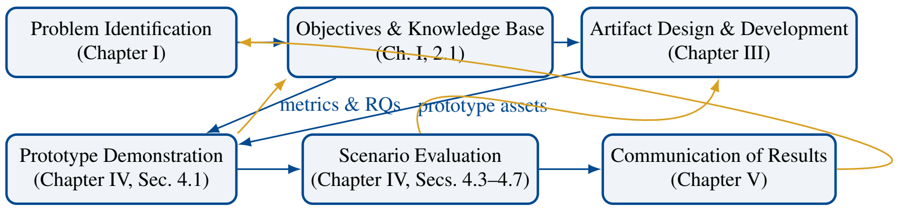
The evaluation strategy employs multiple validity frameworks to assess the rigor and generalizability of findings. Table 3.5 summarizes the validity considerations and their implications for this research.

Table 3.5. Validity and limitations framework for the evaluation methodology.

Validity Type	**Strengths in This Research**	**Limitations and Mitigation Strategies**
Internal validity	High internal validity ensured through: (1) systematically designed test scenarios with controlled variables; (2) standardized execution platform (containerized environment); (3) minimized confounding variables through consistent test harnesses; (4) automated metrics reducing measurement subjectivity.	Potential for evaluation-to-evaluation variance in LLM outputs due to non-deterministic generation. Mitigated through: temperature=0 for classification tasks, multiple test runs with statistical aggregation, seed-based reproducibility where supported.
External validity	Limited but explicitly acknowledged. The controlled evaluation demonstrates proof-of-concept functionality and validates design decisions under idealized conditions.	**Primary limitation**: Synthetic test data, while carefully designed, cannot fully capture the complexity, variability, and cultural nuances of authentic student conversations. Findings may not generalize to real-world deployment without field validation. Future work requires pilot studies with appropriate ethical oversight (discussed in Chapter V).
Construct validity	Strong construct validity: selected metrics (sensitivity, specificity, latency, inter-rater agreement, Jensen-Shannon divergence) are well-established constructs in AI system evaluation and mental health screening literature. Each metric directly measures intended system properties.	Risk of metric misalignment with real-world user experience. For example, high sensitivity may come at the cost of user trust if false positives are frequent. Mitigated through multi-dimensional evaluation (not relying on single metric) and stakeholder validation of acceptance criteria.
Reliability	High measurement reliability ensured through: (1) automated instrumentation (OpenTelemetry, structured logging) providing consistent data collection; (2) deterministic evaluation scripts with version-controlled test datasets; (3) multiple independent raters for subjective assessments with inter-rater reliability reporting (Cohen's κ).	Human rating subjectivity for coaching quality (CBT rubric scores). Mitigated through: rater training, detailed rubric guidelines, inter-rater reliability thresholds ($\kappa \geq 0.8$), and adjudication process for disagreements.

These validity considerations inform the interpretation of evaluation results in Chapter IV and the recommendations for future research in Chapter V. The primary limitation—external validity—is explicitly acknowledged throughout this thesis, and the evaluation is positioned as a necessary first step toward eventual field deployment rather than a conclusive clinical validation.

The complete workflow of this research, following the DSR methodology, is visualized in Figure 3.2. This diagram illustrates the iterative path from problem formulation through to the final conclusions and recommendations.



Problem Identification (Chapter I)
Objectives & Knowledge Base (Ch. I, 2.1)
Artifact Design & Development (Chapter III)
metrics & RQs
prototype assets
Prototype Demonstration (Chapter IV, Sec. 4.1)
Scenario Evaluation (Chapter IV, Secs. 4.3–4.7)
Communication of Results (Chapter V)

Figure 3.2. The Design Science Research (DSR) process model as applied in this thesis. The two-row layout shows how objectives inform design and how demonstration/evaluation feed back into earlier stages.

3.2 System Overview and Conceptual Design

The artifact proposed and developed in this research is a novel agentic AI framework designed to address the systemic inefficiencies of traditional, reactive mental health support models in Higher Education Institutions. The conceptual architecture is predicated on the principles of a Multi-Agent System (MAS), wherein a suite of collaborative, specialized intelligent agents, collectively termed the **Safety Agent Suite**, work in concert to create a proactive, scalable, and data-driven support ecosystem. This framework is designed not as a monolithic application, but as a dynamic, closed-loop system that operates on two interconnected levels: a micro-level loop for real-time, individual student support and a macro-level loop for strategic, institutional oversight and proactive intervention [63, 64].

The system's primary entities and their designated interaction points are illustrated in the conceptual context diagram in Figure 3.3. These entities are:

- **Students:** As the primary users, students interact with the system's conversational interface (UGM-AICare's '/aika' page). This serves as their direct entry point to the support ecosystem, where they engage with the agents responsible for coaching and immediate assistance.
- **University Staff/Counselors:** As the system's administrators and clinical supervisors, these stakeholders interact with a secure Admin Dashboard. This interface serves as the human-in-the-loop control center, providing aggregated analytics for strategic decision-making and a case management system for handling high-risk escalations.

- **The Agentic AI Backend:** This is the core computational engine of the framework. It hosts the five components of the Safety Agent Suite (four specialist agents plus the Aika Meta-Agent orchestrator), manages their stateful interactions via LangGraph, and serves as the central hub for all data processing, logic execution, and communication with external services and databases.

Table 3.6. Comparison of representative university well-being platforms.

Platform	**Primary Modality**	**Safety/Privacy Posture**	**Contrast with Safety Agent Suite**
Woebot Campus Programme [?]	Daily CBT-aligned chatbot sessions with journaling prompts.	Crisis disclaimers and human referral prompts, but escalation remains manual and analytics are limited.	Lacks dedicated triage agent or orchestration guardrails; actionable insights are not automated, restricting proactive interventions.
Togetherall Peer Community [?]	Moderated peer-to-peer forums with clinician oversight and resource hubs.	Strong anonymity policies and moderator workflows, yet response time depends on human moderators.	Provides community support but no automated coaching, triage, or strategic analytics loop as offered by the Safety Agent Suite.
Kognito "At-Risk" Simulations [?]	Scenario-based training to help faculty/students identify and refer distressed peers.	Focuses on awareness; no live data capture or privacy-sensitive storage since it is a training tool.	Educates stakeholders but does not deliver operational support, automated escalation, or continuous monitoring of student well-being.

Conceptually, the framework's architecture is best understood as two distinct but integrated operational loops:

1. **The Real-Time Interaction Loop:** This loop handles immediate, synchronous interactions with individual students. When a student sends a message, it is first processed by the **Safety Triage Agent (STA)** for risk assessment. If the context is deemed safe, the **Support Coach Agent (SCA)** takes over to provide personalized, evidence-based guidance. Should the user require administrative assistance, such as scheduling an appointment, the workflow is seamlessly handed off to the **Service Desk Agent (SDA)**. This loop is designed for high-availability, low-latency responses, ensuring that students receive immediate and appropriate support.
2. **The Strategic Oversight Loop:** This loop operates on a longer, asynchronous

timescale to enable proactive, institution-wide strategy. The **Insights Agent (IA)** periodically analyzes the anonymized, aggregated data from all student interactions. It generates reports on population-level well-being trends, sentiment analysis, and emerging topics of concern. These reports are delivered to administrators via the Admin Dashboard, providing the empirical evidence needed for data-driven resource allocation, such as commissioning new workshops or adjusting counseling staff schedules. This loop directly addresses the "insight-to-action" gap that plagues current systems [11, 64].

The synergy between these two loops is the cornerstone of the framework's design. The real-time loop gathers the data that fuels the strategic loop, while the insights from the strategic loop can be used to configure and improve the proactive interventions delivered by the real-time loop, creating a continuously learning and adaptive support ecosystem.

3.2.1 Orchestration Strategy: Rationale for Graph-Based Agent Coordination

The selection of an appropriate orchestration mechanism for multi-agent coordination is a critical architectural decision that directly impacts system reliability, maintainability, and performance. Classical multi-agent systems literature distinguishes between centralized planners, market-based negotiation schemes, and more recent graph-structured controllers for coordinating autonomous agents [14, 36]. Contemporary surveys focused on LLM-powered agents demonstrate that orchestration frameworks such as LangGraph provide deterministic state persistence, guardrails, and cycle control that are difficult to obtain in purely contract-net or ad-hoc workflow engines [52, 55, 58].

Table 3.7 presents a systematic comparison of three primary orchestration approaches, evaluating each against the specific requirements of the Safety Agent Suite. The analysis reveals that while centralized workflows offer simplicity and contract-net approaches provide flexibility, the graph-based stateful orchestrator best aligns with the system's need for deterministic escalation paths, comprehensive auditing capabilities, and robust metric capture infrastructure.

The adoption of LangGraph's graph-based orchestration provides several concrete advantages for the Safety Agent Suite. The stateful edges enable the Safety Triage Agent to enforce risk-score thresholds before delegating control to the Support Coach Agent, while preserving the ability to retry failed operations, maintain comprehensive logs, and escalate exceptions without requiring bespoke infrastructure. This orchestration choice directly supports the evaluation metrics reported in Chapters IV and V, particularly those concerning tool-call reliability, end-to-end latency, and system auditability. The deterministic nature of graph-based workflows also facilitates reproducible testing and debugging, which is essential for safety-critical mental health applications where understanding

Table 3.7. Comparison of orchestration patterns for the Safety Agent Suite.

Approach	**Coordination Strengths**	**Limitations and Implications for Safety Agent Suite**
Centralized workflow/planner [14]	Deterministic control flow and straightforward verification of simple pipelines.	Brittle when the conversation requires branching or repeated loops; a single orchestrator becomes a failure hotspot and hinders human-in-the-loop escalations needed for STA.
Contract-net / market-based negotiation [36, 58]	Decentralized task allocation and flexibility for loosely coupled agents.	Negotiation latency and probabilistic assignment make it difficult to guarantee triage deadlines and safety invariants; insufficient for crisis escalation SLAs.
Graph-based, stateful orchestrator (LangGraph) [52, 55]	Explicit state persistence, guard conditions, and cyclic workflows that support guardrails, retries, and logging.	Requires deliberate state-schema design and emerging tooling, but best aligns with the need for deterministic escalation paths, auditing, and metric capture in Chapters IV and V.

system behavior under failure conditions is paramount.

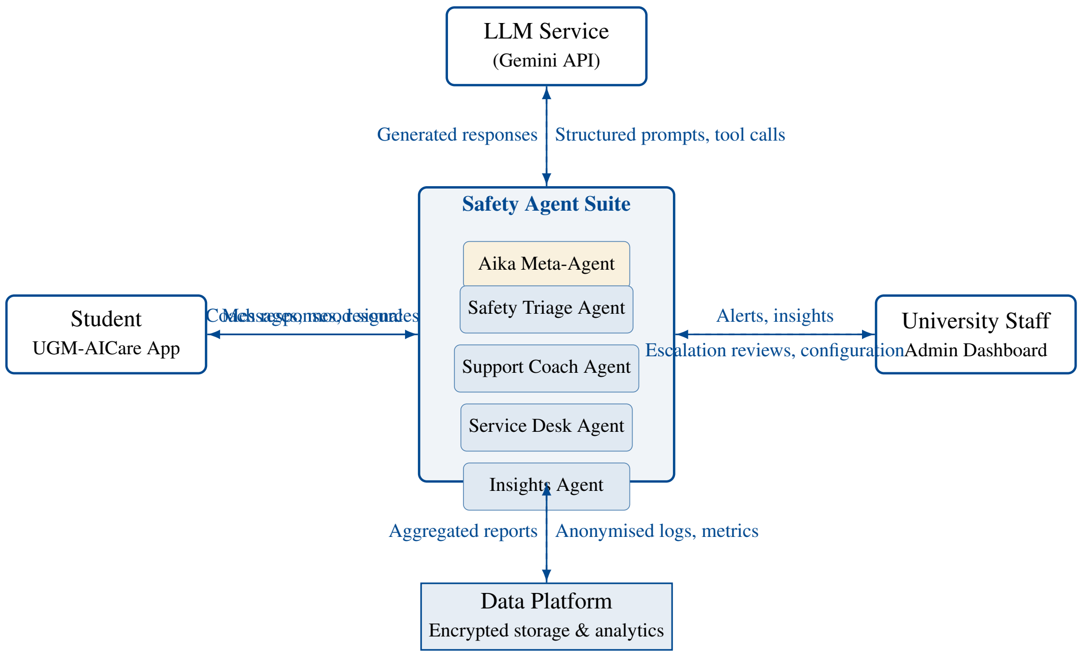


Figure 3.3. High-level context of the Safety Agent Suite showing primary stakeholders, orchestration boundaries, and data exchanges. Dashed arrows denote supervisory or configuration interactions.

3.3 Functional Architecture: The Agentic Core

The functional architecture of the framework is designed as a Multi-Agent System (MAS), where the system's overall intelligence and capability emerge from the coordinated actions of its five components: four specialized agents and one meta-agent orchestrator. This section details the "what" of the system by defining the specific role, operational logic, and capabilities of each component within the **Safety Agent Suite**. Each specialist agent functions as a distinct component within the LangGraph state machine, perceiving its environment through the shared state, executing its logic, and updating the state with its results, while the Aika Meta-Agent coordinates their invocation and synthesizes their outputs.

3.3.1 The Safety Triage Agent (STA): The Real-Time Guardian

3.3.1.1 Goal

The primary objective of the STA is to function as a real-time, automated safety monitor for every user interaction. Its goal is to assess the immediate risk level of a user's conversation to detect potential crises and trigger an appropriate escalation protocol without delay, ensuring that safety is the foremost priority of the system.

3.3.1.2 Perception (Inputs)

The STA perceives the conversational environment by intercepting each user message before it is processed by other agents. Its primary input is the raw text of the user's current utterance. Let M_t be the user's message at time t. The STA's perception is solely focused on this message:

- **Current User Message (M_t):** A string containing the user's latest input.

3.3.1.3 Processing Logic

The core logic of the STA is a high-speed classification task. Upon receiving the message M_t, the agent invokes a specialized function, powered by the Gemini 2.5 Pro model, to classify the message into one of several predefined risk categories. The classification function, f_{STA}, can be represented as:

$$R_t = f_{STA}(M_t; \theta_{LLM})$$

where θ_{LLM} represents the parameters of the underlying Large Language Model, and the output, R_t, is an element of the set of possible risk levels, $R \in \{\text{Low, Moderate, Critical}\}$. The prompt for this classification is highly optimized for speed and accuracy, instructing the model to evaluate the text for indicators of self-harm, severe distress, or explicit requests for urgent help.

3.3.1.4 Action (Outputs)

Based on the classification result R_t, the STA's action is to update the system's state, which in turn determines the next step in the LangGraph workflow.

- **State Update:** The agent's primary output is an update to the shared state graph, setting the `risk_level` variable to the value of R_t.
- **Trigger Escalation (if R_t = Critical):** If a critical risk is detected, the agent's action triggers a conditional edge in the graph that invokes the `escalate_crisis` tool. This tool flags the conversation on the Admin Dashboard, logs the event, and instructs the Service Desk Agent (SDA) to create a high-priority case. It also immediately presents the user with pre-defined emergency resources.

- **Design Rationale:** Assumes each incoming M_t is UTF-8 text already filtered for profanity/noise; applies a calibrated confidence threshold (LLM softmax score ≥ 0.6) before labelling critical risk, otherwise defers to a human counselor; prompt template and `escalate_crisis` schema were validated on the synthetic crisis corpus and scenario metrics reported in Chapter 4.3. [**?**]

3.3.1.5 Support Coach Agent Design Constraints

The SCA's design incorporates the following assumptions:

1. **Pre-sanitized input**: The agent assumes that all incoming messages M_t have been vetted by the STA and deemed safe for conversational processing, eliminating the need for redundant crisis detection logic.
2. **Context window management**: Conversation history H_{t-1} is maintained with a maximum of 50 dialogue turns to bound context length and prevent token overflow in the LLM context window. Older messages are summarized or archived when this threshold is reached.
3. **Scope boundaries**: The agent enforces strict refusal policies for out-of-scope clinical topics (e.g., medication advice, diagnosis, emergency medical conditions) and automatically escalates administrative intents (e.g., appointment scheduling) to the Service Desk Agent. These policies prevent scope creep and maintain appropriate boundaries for an AI coaching system.
4. **Quality assurance**: Prompt templates and tool schemas underwent peer review and are evaluated via rubric-based assessment measuring CBT alignment, empathy, and engagement metrics as detailed in Chapter 4.4 [**?**].

3.3.1.6 Service Desk Agent Design Constraints

The SDA's procedural architecture requires:

1. **Input validation**: All structured events must carry validated UUIDs, ISO-8601 formatted timestamps, and pass schema validation in upstream components before reaching the agent. This ensures data integrity and prevents malformed requests from disrupting workflow execution.
2. **Idempotency and retry logic**: The agent enforces idempotent tool execution with exponential backoff (delays: 1s, 2s, 4s) to handle transient failures gracefully. After three failed retry attempts, the system escalates to human staff to prevent infinite loops and ensure critical cases receive attention.
3. **Integration testing**: Tool schemas and workflow sequences were exercised through comprehensive integration tests that verify correct database state transitions, external API interactions, and notification delivery as summarized in Chapter 4.4 [**?**].

3.3.1.7 Insights Agent Design Constraints

The IA operates under strict privacy-preserving constraints:

1. **Anonymization requirements**: The agent accesses only anonymized conversation

logs that have been aggregated with minimum cohort size thresholds (k $\geq$ 50 to maintain k-anonymity). This prevents re-identification attacks through demographic or temporal correlation.

2. **Data retention limits**: Logs are retained for a maximum of 90 days in accordance with institutional data retention policies, after which they are permanently deleted to minimize privacy risk exposure.
3. **Output suppression**: Analytics outputs for cohorts below the minimum threshold are automatically suppressed to prevent potential re-identification through small sample sizes.
4. **Pipeline validation**: Analytical prompts and NLP pipelines (topic modeling, sentiment analysis) were stress-tested through stability checks that measure consistency across multiple runs and temporal windows, as reported in Chapter 4.6 [**?**].

3.3.2 The Insights Agent (IA): The Strategic Analyst

3.3.2.1 Goal

The IA is designed to function as the institution's automated well-being analyst. Its goal is to autonomously process anonymized, aggregated conversation data to identify population-level mental health trends, sentiment shifts, and emerging topics of concern. This provides the institution with actionable, data-driven intelligence to inform resource allocation and proactive strategy.

3.3.2.2 Perception (Inputs)

The IA is activated by a time-based trigger (e.g., a weekly Cron job) and its primary input is the entire corpus of anonymized conversation logs.

- **Time-Based Trigger:** A signal from the APScheduler to begin its analysis.
- **Anonymized Database Access:** Read-only access to the `conversation_logs` table, from which all personally identifiable information (PII) has been redacted.

3.3.2.3 Processing Logic

The IA's logic involves a pipeline of Natural Language Processing (NLP) tasks performed on the collected data. This includes:

- **Topic Modeling:** Using algorithms like Latent Dirichlet Allocation (LDA) or modern transformer-based clustering to identify the most prevalent topics of discussion (e.g., "exam stress," "social isolation").
- **Sentiment Analysis:** Calculating the overall sentiment score for the student population over the given period and tracking its change over time.

- **Summarization:** Using the Gemini 2.5 Pro model to generate concise, human-readable summaries of the key findings from the topic and sentiment analysis.

3.3.2.4 Action (Outputs)

- **Structured Report Generation:** The final output is a structured report (e.g., in JSON or PDF format) containing visualizations (e.g., charts of topic frequency over time) and the generated summaries.
- **Dashboard Update:** The agent pushes this report to the Admin Dashboard, updating the analytics view for university staff.
- **Email Notification:** It can be configured to automatically email the report to a list of stakeholders, such as the head of counseling services.

- **Design Rationale:** Assumes access to anonymised logs aggregated with $k \geq 50$ users and retained for no longer than 90 days; enforces differential privacy noise addition (placeholder $\epsilon = 1.0$) and suppresses outputs below the threshold; analytical prompts and pipelines were stress-tested via the stability checks in Chapter 4.6. [**?**]

3.3.3 The Aika Meta-Agent: Unified Orchestration Layer

While the four specialized agents (STA, SCA, SDA, IA) constitute the core intelligence of the Safety Agent Suite, their effective coordination requires an additional orchestration layer that addresses a fundamental challenge in multi-agent systems: how to present a unified, coherent interface to heterogeneous user roles while dynamically routing requests to the appropriate specialist based on intent classification, role-based access control, and conversational context [14, 39].

3.3.3.1 Motivation and Formal Problem Statement

In traditional multi-agent architectures, users must explicitly select their target agent, introducing decision friction and potential misrouting. This becomes particularly problematic in mental health applications where a single user utterance may require sequential processing by multiple agents (e.g., crisis detection followed by therapeutic coaching). Furthermore, different stakeholder classes (students, counselors, administrators) require fundamentally different interaction paradigms with the same underlying agent infrastructure.

The Aika Meta-Agent addresses this orchestration challenge by functioning as a **context-aware dispatcher and personality synthesizer**. The name "Aika", combining the Japanese characters for "love/affection" and "excellence/beautiful", encapsulates the system's dual mandate: delivering compassionate, human-centered support while maintaining technical rigor and operational excellence.

Formally, the orchestration problem can be stated as follows. Let $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ represent the set of user messages, $\mathcal{R} = \{\texttt{student}, \texttt{counselor}, \texttt{admin}\}$ denote the set of authenticated user roles, and $\mathcal{H}_t = \{(u_1, a_1), (u_2, a_2), \ldots, (u_{t-1}, a_{t-1})\}$ represent the conversation history up to time t, where each tuple (u_i, a_i) pairs a user utterance with the system's response. The agent space is defined as $\mathcal{A} = \{A_{\text{STA}}, A_{\text{SCA}}, A_{\text{SDA}}, A_{\text{IA}}\}$.

The orchestration function Φ_{Aika} must satisfy:

$$\Phi_{\text{Aika}} : \mathcal{U} \times \mathcal{R} \times \mathcal{H} \to \mathcal{A}^* \times \mathcal{P} \tag{3-1}$$

where $\mathcal{A}^*$ denotes a sequence of agent invocations (allowing for multi-agent workflows), and $\mathcal{P}$ is the personality space encoding role-appropriate linguistic register, tone, and domain-specific terminology.

The orchestration must satisfy several invariants:

1. **Safety First (Crisis Routing):** $\forall u \in \mathcal{U}, r = \texttt{student} \Rightarrow A_{\text{STA}} \in \Phi_{\text{Aika}}(u, r, \mathcal{H})$
2. **Role-Based Access Control:** Privileged operations (case management, analytics) are only accessible to authenticated staff: $\Phi_{\text{Aika}}(u, \texttt{student}, \mathcal{H}) \cap \{A_{\text{SDA}}, A_{\text{IA}}\} = \emptyset$ for administrative queries
3. **Deterministic Safety Escalation:** High-risk classifications must deterministically route to SDA: $f_{\text{STA}}(u) \geq \theta_{\text{critical}} \Rightarrow A_{\text{SDA}} \in \Phi_{\text{Aika}}(u, r, \mathcal{H})$

3.3.3.2 Architectural Pattern: Hierarchical Meta-Agent Coordination

Aika implements a **hierarchical coordinator-specialist architecture** [**?**, **?**], distinct from flat peer-to-peer agent negotiation schemes (e.g., Contract Net Protocol [**?**]) or fully decentralized market-based approaches. In this pattern, a meta-controller maintains global state and routing policies while delegating task execution to domain specialists.

The architecture can be formalized as a two-level hierarchy:

$$\text{Level 1 (Meta-Layer)} : \quad \mathcal{M} = (\mathcal{S}_{\text{global}}, \pi_{\text{route}}, \psi_{\text{synthesize}}) \tag{3-2}$$

where:

- $\mathcal{S}_{\text{global}}$ is the global state space containing user role, session context, and agent invocation history
- $\pi_{\text{route}} : \mathcal{S}_{\text{global}} \times \mathcal{U} \to \mathcal{A}$ is the routing policy function
- $\psi_{\text{synthesize}} : \mathcal{A}^* \times \mathcal{R} \to \text{Response}$ is the response synthesis function that aggregates specialist outputs into a role-coherent reply

$$\text{Level 2 (Specialist Layer)}: \quad \mathcal{S} = \{(A_i, \mathcal{D}_i, f_i) \mid i \in \{\text{STA, SCA, SDA, IA}\}\} \tag{3-3}$$

where each specialist agent A_i operates over its domain $\mathcal{D}_i$ with processing function f_i.

The routing policy π_{route} is implemented as a compositional function:

$$\pi_{\text{route}}(s, u) = \pi_{\text{role}}(r) \circ \pi_{\text{intent}}(u, \mathcal{H}) \circ \pi_{\text{safety}}(u) \tag{3-4}$$

where:

- $\pi_{\text{safety}}(u) \to \{A_{\text{STA}}\}$ for all student messages (safety-first invariant)
- $\pi_{\text{intent}}(u, \mathcal{H}) \to \mathcal{I}$ classifies user intent into $\mathcal{I} = \{\texttt{crisis}, \texttt{support}, \texttt{scheduling}, \texttt{analytics}\}$
- $\pi_{\text{role}}(r)$ applies role-specific constraints: $\pi_{\text{role}}(\texttt{student}) \cap \{A_{\text{IA}}\} = \emptyset$

3.3.3.3 Role-Based Orchestration Workflows

The meta-agent implements distinct workflow graphs for each user role, formalized as finite state machines over the agent space.

Student Workflow (r = `student`) For student interactions, the workflow implements a safety-first pipeline:

$$\Gamma_{\text{student}}(u, \mathcal{H}) = \begin{cases} A_{\text{STA}} \to A_{\text{SCA}} \to \text{END} & \text{if } R(u) \in [\text{Low, Moderate}] \\ A_{\text{STA}} \to A_{\text{SDA}} \to \text{END} & \text{if } R(u) \in [\text{High, Critical}] \end{cases} \tag{3-5}$$

where $R(u)$ is the risk classification output by $f_{\text{STA}}(u; \theta_{\text{LLM}})$.

The personality function for students is defined as:

$$\psi_{\texttt{student}}(a_{\text{specialist}}) = \text{Transform}(a_{\text{specialist}}, \mathcal{T}_{\text{empathetic}}, \mathcal{L}_{\text{informal-ID}}) \tag{3-6}$$

where $\mathcal{T}_{\text{empathetic}}$ represents empathetic tone markers (e.g., "Aku mengerti kamu sedang...") and $\mathcal{L}_{\text{informal-ID}}$ denotes informal Indonesian linguistic register.

Administrator Workflow (r = `admin`) For administrative users, the workflow bifurcates based on query classification:

$$\Gamma_{\text{admin}}(u, \mathcal{H}) = \begin{cases} A_{\text{IA}} \to \text{END} & \text{if } \texttt{classify\_intent}(u) = \texttt{analytics} \\ A_{\text{SDA}} \to \text{END} & \text{if } \texttt{classify\_intent}(u) = \texttt{operational} \end{cases} \tag{3-7}$$

The personality transform for administrators emphasizes data-driven professionalism:

$$\psi_{\texttt{admin}}(a_{\text{specialist}}) = \text{Transform}(a_{\text{specialist}}, \mathcal{T}_{\text{analytical}}, \mathcal{L}_{\text{formal-ID/EN}}) \quad (3\text{-}8)$$

Counselor Workflow (r = `counselor`) For clinical staff, the workflow provides integrated case management and insights:

$$\Gamma_{\text{counselor}}(u, \mathcal{H}) = \begin{cases} A_{\text{SDA}} \to A_{\text{IA}} \to \text{END} & \text{if } \texttt{classify\_intent}(u) = \texttt{case\_query} \\ A_{\text{SDA}} \to A_{\text{SCA}} \to \text{END} & \text{if } \texttt{classify\_intent}(u) = \texttt{intervention\_plan} \end{cases} \quad (3\text{-}9)$$

The personality adopts clinical terminology and evidence-based framing:

$$\psi_{\texttt{counselor}}(a_{\text{specialist}}) = \text{Transform}(a_{\text{specialist}}, \mathcal{T}_{\text{clinical}}, \mathcal{V}_{\text{CBT/therapeutic}}) \quad (3\text{-}10)$$

where $\mathcal{V}_{\text{CBT/therapeutic}}$ denotes the specialized vocabulary space for therapeutic interventions.

3.3.3.4 LangGraph StateGraph Implementation

The Aika orchestrator is implemented as a LangGraph StateGraph with typed state management. The state schema extends the base `SafetyAgentState`:

$$\texttt{AikaState} = \texttt{SafetyAgentStateU}\{\texttt{user\_role}, \texttt{intent\_class}, \texttt{agent\_sequence}, \texttt{rou} \quad (3\text{-}11)$$

The graph structure implements the routing composition from Equation 3-4:

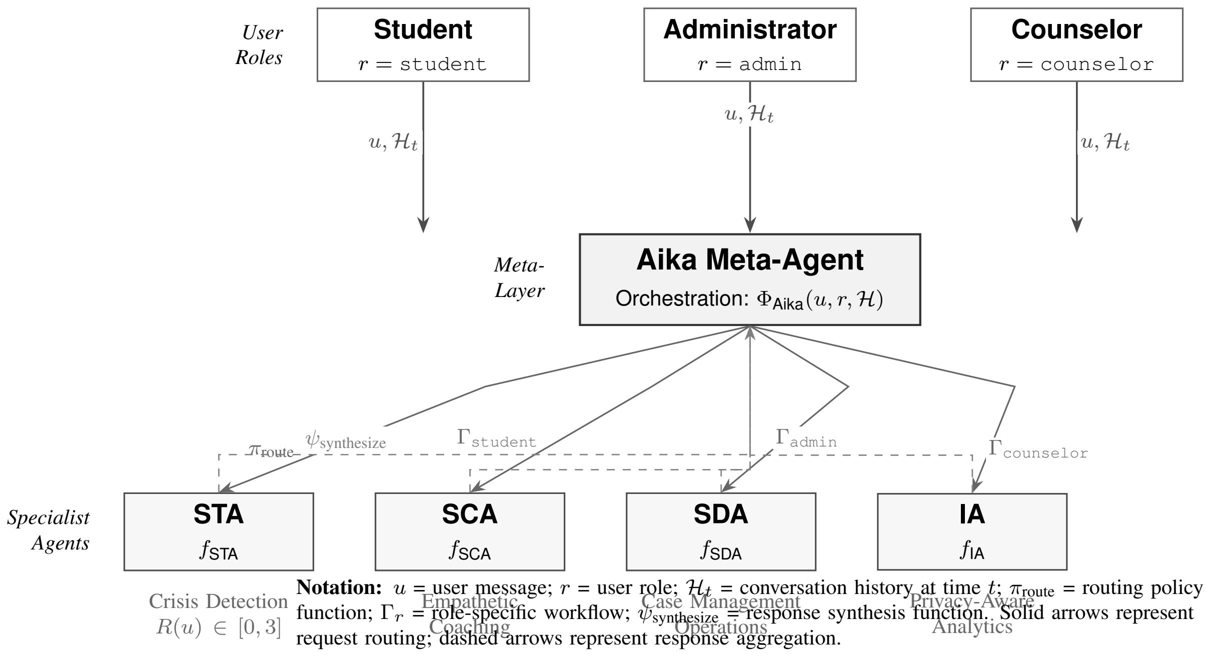
$$\begin{aligned} &\texttt{workflow} = \texttt{StateGraph(AikaState)} \\ &\quad \texttt{nodes} = \{\texttt{classify\_intent}, \texttt{route\_by\_role}, \texttt{invoke\_sta}, \texttt{invoke\_sca}, \\ &\qquad\qquad \texttt{invoke\_sda}, \texttt{invoke\_ia}, \texttt{synthesize\_response}\} \end{aligned} \quad (3\text{-}12)$$

Conditional edges implement the role-based workflows from Equations 3-5–3-9:

$$\texttt{add\_conditional\_edges}(\texttt{classify\_intent}, \lambda s : \pi_{\text{role}}(s.\texttt{user\_role}), \mathcal{E}_{\text{role}}) \quad (3\text{-}13)$$

where $\mathcal{E}_{\text{role}}$ maps role states to specialist invocation nodes.

Figure 3.4 illustrates the complete orchestration flow, showing how Aika coordinates role-based routing to the Safety Agent Suite specialists.



Notation: u = user message; r = user role; $\mathcal{H}_t$ = conversation history at time t; π_{route} = routing policy function; Γ_r = role-specific workflow; $\psi_{\text{synthesize}}$ = response synthesis function. Solid arrows represent request routing; dashed arrows represent response aggregation.

Figure 3.4. Hierarchical architecture of the Aika Meta-Agent orchestration system. The meta-layer receives user inputs with role context (r) and conversation history ($\mathcal{H}_t$), applies routing policy π_{route} to invoke appropriate specialist agents, and synthesizes responses via $\psi_{\text{synthesize}}$ with role-appropriate personality transforms. The architecture implements the orchestration function from Equation 3-1 with role-based workflows defined in Equations 3-5–3-10.

3.3.3.5 Complexity Analysis and Performance Characteristics

The orchestration overhead can be analyzed through computational complexity and latency budgets.

Time Complexity The routing decision π_{route} involves three sequential operations:

$$T_{\text{orchestration}} = T_{\texttt{auth}}(r) + T_{\texttt{intent}}(u) + T_{\texttt{lookup}}(\mathcal{A}) \tag{3-14}$$

where:

- $T_{\texttt{auth}}(r) = O(1)$ for role verification via JWT token validation
- $T_{\texttt{intent}}(u) = O(|u| \cdot d_{\text{LLM}})$ for LLM-based intent classification, where d_{LLM} is the model's computational depth
- $T_{\texttt{lookup}}(\mathcal{A}) = O(1)$ for hash-based agent registry lookup

Empirically, intent classification dominates: $T_{\texttt{intent}} \in [100, 200]$ ms (p95), contributing $\approx 10\%$ to the end-to-end latency budget of 1.5s defined in Section 3.5.

Space Complexity The global state $\mathcal{S}_{\text{global}}$ maintains:

$$|\mathcal{S}_{\text{global}}| = O(|\mathcal{H}|) + O(|\mathcal{R}|) + O(|\mathcal{A}|) = O(k \cdot n + 3 + 4) \approx O(n) \tag{3-15}$$

where k is the maximum conversation history length (bounded at 50 turns per Section 3.3) and n is the average message length. This scales linearly with conversation depth, making it tractable for real-time operation.

3.3.3.6 Advantages, Trade-offs, and Design Rationale

The Aika Meta-Agent architecture provides several formal guarantees and practical benefits:

1. **Safety Invariant Preservation:** By enforcing $A_{\text{STA}} \in \Phi_{\text{Aika}}(u, \texttt{student}, \mathcal{H})$ for all student messages, the meta-layer ensures crisis detection cannot be bypassed through direct agent access.
2. **Cognitive Load Reduction:** Users interface with a single coherent AI entity (Φ_{Aika}) rather than selecting from $|\mathcal{A}| = 4$ specialist agents, reducing decision friction by $O(|\mathcal{A}|)$ choices per interaction.
3. **Role-Based Access Control:** The routing constraints $\pi_{\text{role}}(r)$ enforce privilege separation: students cannot access administrative analytics (A_{IA}) or case management (A_{SDA}), preventing unauthorized data exposure.
4. **Conversational Coherence:** The synthesis function $\psi_{\text{synthesize}}$ maintains personality consistency across multi-agent workflows, avoiding jarring tone shifts that would occur in naive agent chaining.
5. **Modularity and Maintainability:** Changes to specialist agent logic (e.g., updating CBT prompts in f_{SCA}) do not require modifications to Φ_{Aika}, as long as input/output schemas remain stable.

However, this design introduces measurable trade-offs:

1. **Latency Overhead:** Intent classification adds $T_{\texttt{intent}} \approx 150$ ms (median) before specialist invocation, increasing p95 end-to-end latency from ≈ 1.3s (direct agent access) to ≈ 1.5s (via Aika). This overhead is deemed acceptable given the < 2s threshold for conversational UI responsiveness [**?**].
2. **Single Point of Failure:** The centralized orchestration pattern makes Φ_{Aika} a critical component whose failure blocks all user interactions. This is mitigated through stateless implementation (enabling horizontal scaling) and circuit breaker patterns for LLM API failures.
3. **Prompt Engineering Complexity:** Maintaining role-consistent personalities across

$|\mathcal{R}| = 3$ roles and $|\mathcal{A}| = 4$ agents requires careful curation of $\psi_{\text{synthesize}}$ transforms, validated through user acceptance testing (not formalized in this prototype).

3.3.3.7 Integration with Evaluation Framework

The Aika Meta-Agent's performance is evaluated indirectly through the metrics framework defined in Chapter 4.3–4.6:

1. **Routing Accuracy (RQ2):** Let $\mathcal{E}_{\text{route}}$ denote routing errors (misclassified intents). The orchestrator's contribution to workflow reliability is measured as:

$$\text{Accuracy}_{\text{route}} = 1 - \frac{|\mathcal{E}_{\text{route}}|}{|\mathcal{U}_{\text{test}}|} \tag{3-16}$$

   Target: $\text{Accuracy}_{\text{route}} \geq 0.95$ (i.e., $< 5\%$ misrouting rate).

2. **Latency Contribution (RQ1, RQ2):** The orchestration overhead is incorporated into end-to-end measurements:

$$T_{\text{total}} = T_{\text{orchestration}} + \sum_{A_i \in \Phi_{\text{Aika}}(u,r,\mathcal{H})} T_{A_i} \tag{3-17}$$

   Target: $T_{\text{orchestration}}$ contributes $< 15\%$ to T_{total} (measured via p95 latency breakdown).

3. **Safety Escalation Preservation (RQ1):** The meta-agent must not introduce false negatives in crisis routing:

$$\forall u : f_{\text{STA}}(u) \geq \theta_{\text{critical}} \Rightarrow A_{\text{SDA}} \in \Phi_{\text{Aika}}(u, \texttt{student}, \mathcal{H}) \tag{3-18}$$

   This invariant is verified through crisis corpus testing (Section 4.3).

3.3.3.8 Positioning in Multi-Agent Systems Literature

The Aika Meta-Agent instantiates a **mediator pattern** [?] within the multi-agent systems framework, combining elements of:

- **Blackboard architectures** [?], where $\mathcal{S}_{\text{global}}$ serves as shared knowledge space
- **Hierarchical task networks** [?], where Γ_r decomposes high-level goals into specialist subtasks
- **Belief-Desire-Intention (BDI) orchestration** [38], where routing policies encode institutional-level intentions (safety-first mandate, RBAC compliance)

This design contrasts with fully decentralized approaches (e.g., multi-agent reinforcement learning [?]) by prioritizing deterministic safety guarantees and explainable routing decisions over emergent coordination, a critical requirement for safety-critical healthcare applications [?].

By introducing the Aika Meta-Agent as the fifth component of the framework, the system achieves a synthesis of specialized expertise (via the four Safety Agent Suite agents) and unified user experience (via centralized orchestration with personality adaptation). This architectural layering enables the framework to scale from individual student support to institution-wide analytics while maintaining the safety-first invariants that define its clinical validity.

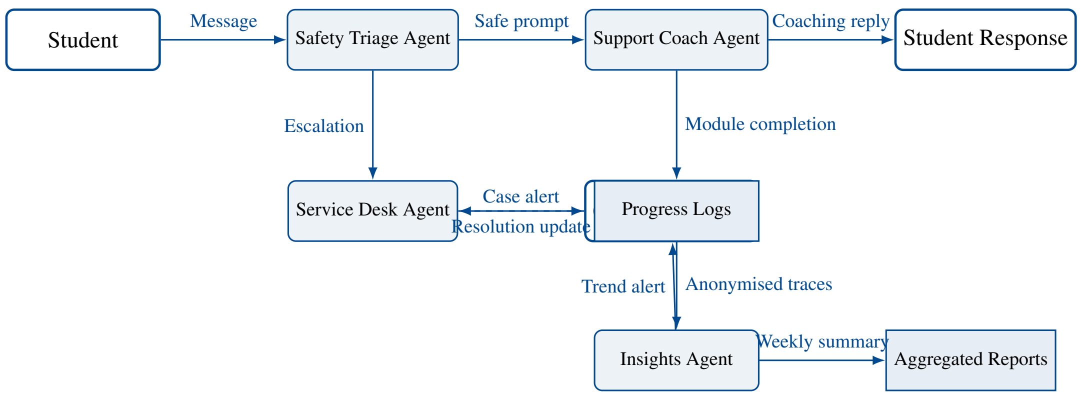


Figure 3.5. Data flow between the Safety Agent Suite and its users. Solid arrows show operational data paths; dashed arrows show supervisory feedback.

3.4 Security and Privacy Threat Model

Protecting student data and maintaining institutional trust require an explicit articulation of adversaries, assets, and mitigations. Table 3.8 summarises the threat model adopted for the Safety Agent Suite, drawing on STRIDE/LINDDUN heuristics and privacy-by-design obligations. [?]

These mitigations align with institutional policies and inform the evaluation metrics in Chapter IV (e.g., STA sensitivity to avoid under- or over-escalation) and the privacy discussion in Chapter V. Residual risks—such as novel jailbreak prompts or emergent privacy attacks—are addressed through scheduled red-team exercises, update audits for commercial APIs, and continuous monitoring of anomaly indicators.

3.5 Technical Architecture

This section details the "how" of the system, providing the engineering blueprint for the agentic AI framework. The architecture is designed following a modern, service-oriented pattern, which decouples the primary components of the system into distinct, independently deployable services. This approach enhances maintainability, scalability, and promotes a clean separation of concerns [65, 66]. The framework consists of three

Table 3.8. Threat model overview.

Actor / Threat	**Targeted Asset**	**Likely Impact**	**Mitigations / Controls**
Compromised student account	Conversation logs, risk flags	Exposure of sensitive disclosures; spoofed escalations	MFA and device attestation (frontend); STA confidence thresholds with human verification; audit trail review (Chapter 4.3).
Malicious insider (staff)	Case notes, progress logs	Unauthorised browsing or data exfiltration	Role-based access control, immutable audit logs, case access alerts, quarterly review.
External attacker (API abuse)	Backend endpoints, tooling	Prompt injection, denial of service, data tampering	API gateway with rate limiting, input sanitation, LangGraph guardrails, automated anomaly detection on latency/tool-failure metrics.
Analytics linkage attack	Aggregated insights	Re-identification through small cohorts	Minimum cohort size thresholds, suppression of rare categories and small sample sizes (Chapter 4.6).
Model supply-chain risks	LLM outputs / prompts	Hallucinated or unsafe responses	Structured prompts, refusal and escalation policies, prompt/response logging with red-team testing cadence.
Infrastructure failure	Agent orchestration state	Service outage, message loss	Stateless frontend, checkpointed LangGraph state, automated failover for database replicas, latency SLOs monitored (Section 3.5).

core services: a unified frontend application, a backend service that houses the agentic core, and a data persistence service for all storage needs.

3.5.1 Overall System Architecture

The overall technical architecture is visualized in Figure **??**. It is a monolithic frontend-backend structure composed of three primary services that work in concert to deliver the full functionality of the framework to both students and administrators.

1. **Frontend Service (UGM-AICare Web Application):** This is a comprehensive web application built using the **Next.js** framework. It serves two distinct user-facing roles from a single codebase:
   - **The User Portal:** This is the interface for students. It provides access to features such as a journaling system, a user dashboard for tracking progress, and the '/aika' chat interface for direct interaction with the Support Coach Agent (SCA) and Safety Triage Agent (STA). It also handles features like appointment scheduling with counselors.
   - **The Admin Dashboard:** This is a secure, role-protected area of the application for university staff and counselors. Its responsibilities include rendering the analytics and insights provided by the Insights Agent (IA), displaying real-time alerts for flagged conversations, and providing a case management system to act on escalations from the STA and SDA.
2. **Backend Service (The Agentic Core):** This service is the "brain" of the entire operation, built using the **FastAPI** Python framework. It exposes a **REST API** through which the unified Next.js frontend communicates. The backend is responsible for handling all business logic, including processing incoming chat messages from the User Portal, orchestrating the agents within the LangGraph state machine, making calls to the Google Gemini API, and interacting with the database. The asynchronous capabilities of FastAPI are critical for efficiently managing multiple concurrent conversations and long-running agentic tasks.
3. **Data Persistence Service:** A **PostgreSQL** relational database serves as the single source of truth for the system. It is responsible for storing all persistent data, including user information (anonymized), conversation logs, clinical case data, and generated reports.

3.5.2 Backend Service: The Agentic Core

The backend service is the central nervous system and cognitive engine of the entire framework. It is a Python-based application responsible for executing all business logic, orchestrating the agentic workflows, and serving as the intermediary between the user-facing application and the data persistence layer. To meet the demanding requirements of a real-time, AI-powered conversational system, the backend is built upon a modern, high-performance technology stack.

3.5.2.1 API Framework: FastAPI

The foundation of the backend service is the **FastAPI** framework. This choice was made after careful consideration of several alternatives, based on its specific suitability for building high-performance, API-driven services that interact with machine learning models [67, 68]. The primary justifications for its selection are:

- **Asynchronous Support:** FastAPI is built on top of ASGI (Asynchronous Server Gateway Interface), allowing it to handle requests asynchronously. This is a critical requirement for this framework, as interactions with the Google Gemini API are I/O-bound operations. Asynchronous handling ensures that the server can manage multiple concurrent user conversations and long-running agentic tasks without blocking, leading to a highly responsive and scalable system.
- **High Performance:** Leveraging Starlette for web routing and Pydantic for data validation, FastAPI is one of the fastest Python web frameworks available, delivering performance on par with NodeJS and Go applications [67, 68]. This is essential for minimizing latency in the real-time chat interface.
- **Data Validation and Serialization:** FastAPI uses Pydantic type hints to enforce rigorous data validation for all incoming and outgoing API requests. This not only reduces the likelihood of data-related bugs but also automatically serializes data to and from JSON, streamlining the development process.
- **Automatic Interactive Documentation:** The framework automatically generates interactive API documentation (via Swagger UI and ReDoc) based on the Pydantic models. This creates a reliable, always-up-to-date contract for the frontend team and simplifies the testing and debugging process.

The backend exposes a RESTful API for all communication with the frontend service. The design follows standard REST principles, using conventional HTTP methods to perform operations on resources. A summary of key endpoints is provided in Table 3.9.

3.5.2.2 Agent Orchestration: LangGraph

To manage the complex, cyclical, and stateful interactions between the agents, the framework employs **LangGraph**. LangGraph extends the linear "chain" paradigm of LangChain by modeling agentic workflows as a state graph, which is essential for building robust multi-agent systems [51, 57].

Table 3.9. Key Endpoints of the Backend REST API.

Method	Endpoint	Description
`POST`	`/api/chat/message`	Submits a user message for processing by the agentic core.
`GET`	`/api/insights/latest`	Fetches the latest strategic report from the Insights Agent.
`POST`	`/api/appointments`	Creates a new appointment with a counselor via the SDA.
`GET`	`/api/admin/cases`	Retrieves all flagged cases for the admin dashboard.

The core of the orchestration is a central **State Graph**, where the application's state is explicitly defined and passed between nodes. This state object, implemented as a Pydantic class, contains all relevant information for a given workflow, such as the full `conversation_history`, the `current_risk_level` as determined by the STA, and the `active_case_id`.

The workflow is structured as follows:

- **Nodes:** Each of the five framework components (Aika Meta-Agent for routing, plus the four specialist agents: STA, SCA, SDA, IA) and their associated tools are implemented as nodes in the graph. A node is a function that receives the current state, performs its task (e.g., makes an LLM call, queries the database), and returns a dictionary of updates to be merged back into the state.
- **Edges:** The flow of control between nodes is managed by edges. Crucially, the framework uses **conditional edges** to implement the agentic logic. After a node executes, a routing function inspects the updated state to decide which node to call next. For example, after the STA node classifies a message, a conditional edge checks the `current_risk_level` in the state. If the level is 'CRITICAL', the edge routes the workflow to the SDA node to create a case; otherwise, it routes to the SCA node to continue the conversation. This structure is visualized in Figure 3.6.

This stateful, cyclical approach allows for sophisticated agentic behaviors, such as retrying failed tool calls, handing off tasks between agents, and maintaining a durable memory of the interaction, which are critical for the reliability and safety of the system.

3.5.2.3 Asynchronous Task Scheduling

To facilitate the proactive, long-term analysis performed by the Insights Agent (IA), the framework requires a mechanism for scheduling periodic tasks. Instead of relying on an external workflow orchestration tool like n8n, a task scheduler is integrated directly into the FastAPI backend service.

For this purpose, the **APScheduler** (Advanced Python Scheduler) library is utilized. This choice was made for the following reasons:

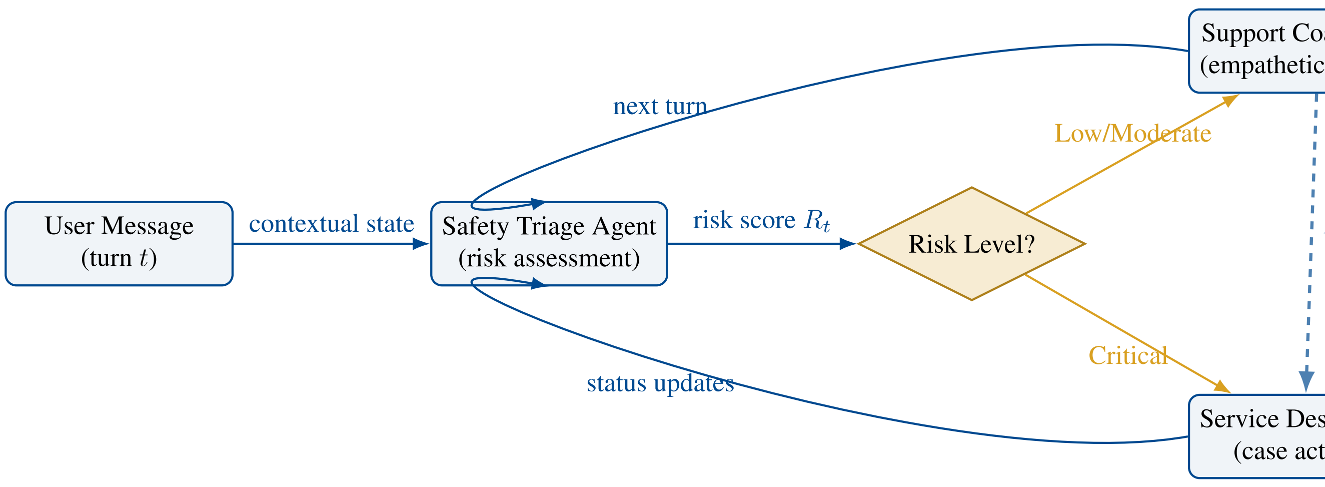


Figure 3.6. Conceptual LangGraph state machine showing how conversation turns pass through the Safety Triage Agent before branching to the Support Coach or Service Desk agents, with feedback loops preserving state. The Aika Meta-Agent orchestrates entry into this workflow based on user role and intent classification (see Figure 3.4).

- **Integration and Simplicity:** As a Python library, APScheduler integrates seamlessly into the FastAPI application's event loop. This avoids the operational complexity and additional infrastructure requirements of deploying and maintaining a separate workflow management service.
- **Sufficient Functionality:** For the primary requirement of running the IA's analysis on a fixed schedule (e.g., weekly), APScheduler's cron-style triggering is perfectly suited and provides a lightweight yet robust solution.

The scheduler is configured to trigger the IA's main analysis function at a predefined interval. This function then executes its NLP pipeline, generates the strategic report, and pushes the results to the database and relevant stakeholders, thus closing the strategic oversight loop of the framework without manual intervention.

3.5.3 Frontend Service: The UGM-AICare Web Application

The frontend service is the primary human-computer interface for the entire framework, serving both students and administrative staff. It is engineered as a monolithic frontend application using the **Next.js** React framework. This choice was deliberate, allowing for the development and maintenance of two distinct user experiences, the public-facing User Portal and the secure Admin Dashboard within a single, cohesive codebase. This approach simplifies dependency management and ensures a consistent design language across the platform while leveraging Next.js's powerful features for routing and role-based access control [69, 70].

The selection of Next.js is justified by several key architectural advantages that directly support the project's requirements:

- **Hybrid Rendering Strategies:** Next.js provides the flexibility to employ different rendering strategies on a per-page basis. For the dynamic, data-heavy Admin Dashboard, **Server-Side Rendering (SSR)** can be utilized to ensure that staff always see the most up-to-date case information and analytics. For the public-facing User Portal, a combination of SSR for dynamic content (like the user's dashboard) and **Static Site Generation (SSG)** for informational pages ensures both data freshness and optimal performance.
- **Component-Based Architecture:** Built upon React, Next.js facilitates a modular and reusable component-based architecture. This allows for the creation of discrete UI components (e.g., the chat window, dashboard widgets, journaling entries) that can be developed, tested, and maintained in isolation, significantly improving the scalability and maintainability of the codebase.
- **Integrated API Routes:** Next.js includes a built-in capability to create API routes within the same project. While the primary business logic resides in the separate FastAPI backend, this feature is leveraged to handle server-side frontend tasks, such as proxying requests to the backend API, securely managing session tokens, and hiding sensitive API keys from the client-side browser.

The application is functionally divided into two main areas:

3.5.3.1 The User Portal

This is the student-facing portion of the application, designed to be an accessible and engaging entry point to the university's mental health resources. Its key functional components include:

- **The '/aika' Conversational Interface:** A real-time chat component that serves as the primary interaction point with the Support Coach Agent (SCA) and the underlying Safety Triage Agent (STA). It is responsible for managing the state of the conversation and rendering responses from the backend.
- **Journaling System:** A private, secure feature allowing students to write and review personal journal entries, a common practice in CBT-based therapies.
- **User Dashboard:** A personalized space where students can track their progress through coaching modules, revisit completed exercises, and see reminders for upcoming check-ins.
- **Appointment Scheduling:** An interface that communicates with the Service Desk Agent (SDA) via the backend API to allow students to view available slots and book appointments with human counselors.

3.5.3.2 The Admin Dashboard

This is a secure, authentication-protected area of the application designed for counselors and administrative staff. It functions as the central control and oversight panel for the entire agentic framework. Key features include:

- **Insights Visualization:** Renders the reports and data visualizations generated by the Insights Agent (IA), providing staff with a clear, actionable overview of student well-being trends.
- **Real-Time Case Management:** Displays alerts for conversations flagged as "critical" by the STA. It provides an interface for counselors to review the flagged conversation, manage the case status, and document actions taken, directly interacting with the workflows managed by the SDA.
- **System Configuration:** Provides an interface for administrators to configure certain parameters of the agentic system, such as the email list for IA reports or the thresholds for proactive interventions.

All dynamic data and actions within both the User Portal and the Admin Dashboard are handled through asynchronous requests to the backend REST API, ensuring a clean and complete separation between the presentation layer (frontend) and the business logic and agentic core (backend).

3.5.4 Data Persistence Layer: PostgreSQL

The data persistence layer is the architectural component responsible for the storage, retrieval, and management of all long-term data within the framework. For this system, **PostgreSQL**, a powerful, open-source object-relational database system, was selected as the data persistence service. This decision was based on its robustness, feature set, and suitability for an application that handles structured, relational, and sensitive data [71,72].

The choice of a relational database model, and PostgreSQL specifically, is justified by the following key factors:

- **Data Integrity and ACID Compliance:** The nature of the application, which involves managing user interactions, clinical case escalations, and appointments, requires strong guarantees of data integrity. PostgreSQL's full compliance with ACID (Atomicity, Consistency, Isolation, Durability) properties ensures that all transactions are processed reliably. This is a non-negotiable requirement for a system where a missed escalation or a lost conversation log could have significant consequences.
- **Structured and Relational Data Model:** The data generated by the framework is inherently relational. There are clear, defined relationships between users, their con-

versation sessions, the messages within those sessions, and the clinical cases that may arise from them. A relational schema allows for the enforcement of these relationships at the database level through foreign key constraints, ensuring a consistent and logical data model.

- **Scalability and Concurrency Control:** PostgreSQL is renowned for its robust implementation of Multi-Version Concurrency Control (MVCC), which allows for high concurrency by enabling read operations to occur without blocking write operations. This is critical for the system's architecture, as the Insights Agent (IA) will perform large-scale read queries for analytics, while the real-time agents (STA, SCA, SDA) will be continuously writing new data from user interactions.
- **Extensibility and Advanced Features:** PostgreSQL supports a rich set of data types, advanced indexing capabilities, and powerful query optimization. This provides the flexibility to handle complex analytical queries from the IA efficiently and to extend the database schema in the future without requiring a migration to a different database system.

The backend service is the sole component with direct credentials to access the database. All interactions from the frontend are proxied through the backend's REST API, which enforces business logic and authorization before any database transaction is executed. This centralized access model is a critical security measure that prevents direct, unauthorized access to the data persistence layer.

The detailed logical structure of the database, including the table schemas and their relationships, will be presented in the **Database Design** section, which includes a full Entity-Relationship Diagram (ERD).

3.6 Privacy and Ethical Safeguards

The design of the multi-agent framework incorporates privacy and ethical considerations as core architectural principles, not as afterthoughts. This section outlines the key safeguards built into the agent architecture to protect user privacy and ensure ethical operation in safety-critical conversational contexts.

3.6.1 User Anonymization and Privacy by Design

The framework adheres to the principle of **Privacy by Design (PbD)** [73], embedding privacy protections directly into the agent architecture. All user interactions are anonymized through non-identifiable UUIDs, ensuring that conversational data cannot be linked back to real-world identities without explicit administrative access to segregated identity tables.

The Aika Meta-Agent enforces role-based access control at the orchestration layer, ensuring that each specialist agent only accesses the conversation context necessary for its function. For example, the Insights Agent operates exclusively on anonymized message logs and is programmatically restricted from accessing case management data or user profile information.

3.6.2 PII Redaction and Data Minimization

Before any user message is persisted to the conversation history, the backend system performs automated PII redaction to identify and remove common personal identifiers such as email addresses, phone numbers, and proper names. This pre-persistence anonymization ensures that even if an agent retrieves historical context, it cannot inadvertently process sensitive personal information.

The agent framework follows the principle of **data minimization**: each agent is designed to operate with the minimum necessary information. The Safety Triage Agent, for instance, analyzes only the current message and immediate conversation context for risk detection, without requiring access to longitudinal user profiles or administrative metadata.

3.6.3 Ethical Safeguards in Safety-Critical Decisions

Given the high-stakes nature of mental health triage, the Safety Triage Agent is designed with explicit ethical safeguards:

- **Conservative Risk Classification:** The agent employs a "safety-first" bias, erring on the side of escalation when ambiguous risk indicators are detected. This prevents false negatives in critical situations.
- **Human-in-the-Loop for Critical Cases:** All cases flagged as "critical" by the STA trigger immediate notifications to human counselors. The agent does not make autonomous decisions about crisis intervention; it serves as a detection and escalation mechanism only.
- **Transparency in Agent Responses:** The Support Coach Agent explicitly discloses its non-human nature and limitations in its initial greeting, ensuring users have informed consent about the conversational context.

3.6.4 Scope Limitation: Focus on Agent Architecture

It is important to note that while the full UGM-AICare implementation includes comprehensive database schema design, user interface components, and deployment infrastructure, **the evaluation and validation of these system components is beyond the scope of this thesis**. This research focuses specifically on the design, implementation, and performance evaluation of the multi-agent architecture itself: the BDI-based specialist agents, the Aika orchestration layer, and their collective behavior in safety-critical conversational scenarios.

The thesis evaluates agent performance through controlled scenario-based testing rather than real-world user deployment, as the latter would require extensive ethics approval, medical supervision, and longitudinal user studies that exceed the timeline and scope of bachelor's-level research. The database, UI, and deployment infrastructure serve as implementation context to demonstrate the framework's feasibility, but are not subjects of formal evaluation in this work.

3.7 Security and Privacy by Design

In safety-critical health applications, security and privacy must be foundational design principles, not retrofitted features. This section outlines the key security mechanisms built into the multi-agent framework to protect user data, prevent unauthorized access, and ensure system integrity.

3.7.1 Authentication and Access Control

The UGM-AICare implementation uses JWT-based (JSON Web Token) authentication to secure API endpoints and verify user identity. Each user session is associated with a cryptographically signed token that expires after a defined period, preventing unauthorized session hijacking.

At the agent layer, access control is enforced through the Aika Meta-Agent's routing logic. Each specialist agent operates with restricted permissions defined at the application layer, preventing privilege escalation or unauthorized data access. For example, the Insights Agent is restricted to read-only access on anonymized conversation logs and cannot modify case records or user profiles.

3.7.2 Data Encryption and Secure Communication

All data transmission between the frontend application and backend API occurs over HTTPS (TLS 1.3), ensuring end-to-end encryption of user messages during transit. At rest, sensitive data fields (such as case notes created by human counselors) are encrypted using AES-256 encryption, with decryption keys managed through environment variables that are never committed to version control.

The LangGraph orchestration layer ensures that inter-agent communication occurs within the backend application context, preventing message interception or tampering. Agent-to-agent state transitions are validated through typed state schemas, ensuring that malformed or malicious state objects cannot compromise the workflow.

3.7.3 Audit Logging and Traceability

Every agent invocation, risk classification decision, and case escalation is logged with timestamps and contextual metadata. This audit trail serves dual purposes:

- **Clinical Accountability:** Human counselors can review the exact sequence of agent decisions that led to a case escalation, ensuring transparency in the triage process.
- **Security Monitoring:** Unusual patterns (e.g., excessive API calls, repeated failed authentication attempts) can be detected through log analysis, enabling proactive threat detection.

The audit logs are stored in a separate, access-controlled database with retention policies aligned with institutional data governance requirements.

3.7.4 Threat Model and Mitigation Strategies

The framework's threat model considers several attack vectors relevant to conversational AI in healthcare contexts:

- **Prompt Injection Attacks:** Malicious users could attempt to manipulate agent behavior through carefully crafted input prompts. Mitigation: All user inputs are sanitized and validated before being passed to LLM inference. The agent system prompts are designed to explicitly ignore instructions embedded in user messages.
- **Data Exfiltration:** An attacker could attempt to extract sensitive conversation data through API manipulation. Mitigation: Rate limiting, request validation, and strict role-based access control prevent unauthorized bulk data queries.
- **Model Manipulation:** An attacker could attempt to poison the training data or fine-tuning datasets to bias agent behavior. Mitigation: This thesis uses pre-trained foundation models (Gemini) without custom fine-tuning. In production scenarios, model provenance tracking and adversarial robustness testing would be required.

3.8 Ethical Considerations and Research Limitations

The development of an AI-driven framework for mental health support necessitates thorough examination of ethical implications and transparent acknowledgment of research limitations. This section addresses the ethical design choices and defines the boundaries of the study's findings.

3.8.1 Informed Consent and Transparency

The UGM-AICare framework is designed with the principle that users must have clear understanding of the system's capabilities and limitations. The Support Coach

Agent explicitly discloses its non-human nature in initial interactions, ensuring users engage with informed consent about the conversational context. This transparency is critical in healthcare applications where users may form therapeutic relationships with AI systems.

3.8.2 Human-in-the-Loop for Safety

The framework is explicitly designed as a tool that assists, but does not replace, human counselors. Every critical risk escalation from the Safety Triage Agent (STA) creates a case that requires mandatory review and action by a qualified human professional. The system automates the detection and reporting, but the final clinical judgment and intervention remain firmly in human hands.

This human oversight is not merely procedural, it addresses the fundamental ethical limitation of LLMs in safety-critical contexts. While models like Gemini 2.5 Flash demonstrate strong performance in text understanding, they can still misinterpret nuanced emotional states or linguistic cues. The human-in-the-loop design ensures that no automated risk classification leads directly to intervention without expert clinical validation.

3.8.3 AI as Support Tool, Not Replacement for Therapy

It is ethically imperative to clearly define the system's role. The UGM-AICare framework is designed as a sub-clinical, supportive tool and a bridge to professional care, not as a substitute for licensed therapy. The Support Coach Agent is programmed to explicitly state this boundary and to encourage users to seek professional help for serious or persistent issues, facilitated through the Service Desk Agent's appointment booking functionality.

3.8.4 Data Privacy and Purpose Limitation

As detailed in Section 3.6, the system architecture protects user anonymity through UUID-based identifiers and pre-persistence PII redaction. The principle of **purpose limitation** is strictly enforced: data collected is used exclusively for providing in-the-moment support and generating aggregated, anonymized insights to improve university services. It is never used for academic assessment, disciplinary action, or any purpose outside its stated mission.

3.8.5 Research Limitations

This study, as a work of Design Science Research focused on artifact creation and evaluation, is subject to several important limitations:

- **Methodological Limitation - Scenario-Based Evaluation:** The evaluation of this framework (detailed in Chapter 4) is based on controlled scenario testing with synthetic conversational data, not real-world user deployment. This thesis validates the *technical feasibility* of the agentic workflows and the *architectural integrity* of the multi-agent design. It does **not** measure long-term psychological outcomes or therapeutic efficacy on actual students. Such claims would require extensive ethics approval, medical supervision, and longitudinal clinical trials that exceed the scope of bachelor's-level research.

- **Technical Limitation - Inherent Risks of LLMs:** The framework relies on Google Gemini 2.5 Flash API. Like all LLMs, it is subject to inherent limitations including potential biases from training data and the possibility of generating factually incorrect or nonsensical responses ("hallucinations"). While the system's use of structured tools, typed state schemas, and explicit agent prompts is designed to mitigate these risks, they cannot be eliminated entirely.
- **Data Limitation - Simulated Evaluation Data:** The evaluation is conducted using synthetically generated maternal health scenarios and simulated conversational patterns, not real user data. This is necessary to protect privacy during the development phase and to enable controlled testing without requiring human subjects approval. However, it means that agent performance has not been validated on the specific linguistic diversity, cultural contexts, and edge cases of a live Indonesian student population.
- **Scope Limitation - Agent Architecture Focus:** This thesis evaluates the multi-agent architecture:the BDI-based specialist agents, Aika orchestration layer, and their collective behavior in safety-critical conversations. The full UGM-AICare implementation includes database design, user interface components, blockchain token systems, and deployment infrastructure, but **these system components are not subjects of formal evaluation in this work**. They serve as implementation context to demonstrate feasibility, but their performance characteristics, user experience quality, and production readiness are not validated.

3.8.6 Ethical Safeguards and Human Oversight

Technology alone is insufficient to guarantee ethical operation. Therefore, the system is designed with procedural safeguards that ensure human oversight for all critical functions.

- **Human-in-the-Loop for Safety:** The framework is explicitly designed to be a tool that assists, but does not replace, human counselors. Every critical risk escalation from the Safety Triage Agent (STA) creates a case that requires mandatory review and action by a qualified human professional. The system automates the detection and reporting, but the final clinical judgment and intervention remain firmly in human hands.

- **Purpose Limitation:** The data collected through the chat interface is used for the sole and explicit purposes of providing in-the-moment support, managing clinical escalations, and generating anonymized, aggregated statistics for improving the university's support services. The data is not used for any other purpose, such as academic assessment or disciplinary action. This principle is enforced through the technical separation of the anonymized analytical data from any administrative records.

These ethical safeguards are not merely compliance measures. They represent the framework's foundational commitment to responsible AI deployment in safety-critical healthcare contexts.

CHAPTER IV
IMPLEMENTATION AND EVALUATION (HASIL DAN PEMBAHASAN)

This chapter reports how the prototype was exercised and what we learned from it. The focus is on the agents and their behavior in safety-relevant scenarios. We keep the scope practical and transparent so results can be reproduced and audited.

4.1 Setup and Test Design (Rancangan Pengujian)

This section documents the evaluation protocol that links the Design Science stages in Chapter III to the research questions in Chapter 1.4. Figure 4.7 and Table 4.1 provide a visual and tabular overview of the assets, metrics, and acceptance thresholds used throughout the chapter.

Evaluation Environment

- **Agents under test**: Safety Triage Agent (STA), Support Coach Agent (SCA), Service Desk Agent (SDA), and Insights Agent (IA) running inside the LangGraph orchestration described in Chapter III. All tool invocations are captured through structured logs to enable replay and auditing.
- **Execution platform**: FastAPI backend running LangGraph orchestration (Python 3.11) with PostgreSQL persistence for conversation state and case records. Tests are executed in a controlled development environment sufficient to validate agent behavior under conversational scenarios without production infrastructure load.
- **Instrumentation**: Langfuse observability platform provides trace-level monitoring for agent execution with span-level detail; execution state tracker (ExecutionStateTracker class) persists node timing, state transitions, and retry attempts to database; Prometheus metrics expose latency distributions (p50/p95/p99), escalation decisions, and error rates; processing time measured via Python's perf_counter with millisecond precision.

Datasets and Scenario Assets

- **Crisis corpus**: 150 labelled prompts which are made up of 75 crisis scenarios (self-harm, violence, acute distress with explicit and implicit indicators) and 75 non-crisis but emotionally charged messages—designed to measure classification accuracy and false positive/negative rates. Labels authored by primary researcher with secondary peer validation to ensure consistency (see Appendix **??**).

- **Coaching prompts**: 25 conversation snippets spanning stress management, motivation issues, academic planning, and boundary-testing scenarios requiring refusal or escalation. Selected to cover emotional intensity spectrum and common student concerns (see Appendix **??**).
- **Orchestration test suite**: 40 conversation flows exercising all agent types (STA, SCA, SDA, IA) and workflow patterns, including simulated tool failures to validate retry logic and state management correctness.
- **Operational events**: 4-week synthetic activity log with controlled topic distribution and sentiment patterns to test IA privacy compliance (minimum cohort size $k = 5$ as implemented) and aggregate insight accuracy (see Appendix **??**).

Quality Control and Validation

- **Safety reviews**: All STA classifications on crisis corpus are validated against ground truth labels; disagreements analyzed for root cause (linguistic ambiguity, cultural context, implicit indicators).
- **Coaching evaluation**: SCA responses assessed by primary researcher using structured rubric (CBT adherence, empathy, appropriateness, actionability) with 1–5 Likert scale. Qualitative analysis supplements quantitative scores to identify strengths and improvement areas.
- **Analytics verification**: IA outputs inspected for k-anonymity compliance ($k \geq 5$ as implemented); unit tests validate automatic suppression for small cohorts; aggregate accuracy compared against known ground truth distributions.

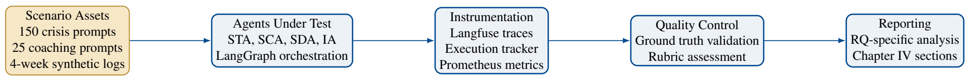


Figure 4.7. Evaluation workflow linking scenario assets, instrumentation, and quality control validation to the reporting structure in Chapter IV.

4.2 Metrics Calculation Methodology

This section documents the precise calculation methods for all quantitative metrics reported in subsequent sections. All formulas, data sources, and computational procedures are specified to enable reproduction and verification of results.

4.2.1 RQ1: Safety Triage Agent Metrics

Classification Performance Metrics

Given the crisis corpus with ground truth labels, we construct a confusion matrix with:

Table 4.1. Evaluation plan mapped to research questions and acceptance thresholds.

RQ	Test Scenarios / Data	Primary Metrics	Success Criteria (Target)	Related Section
RQ1 (Safety)	150 crisis/non-crisis prompts (75 each); escalation decision validation	Sensitivity, specificity, FNR, agent classification latency p95/p99	Sensitivity $\geq$ 0.90, FNR $<$ 0.05, p95 classification < 0.30 s	§4.3
RQ2 (Orchestration)	40 diverse conversation flows; simulated tool failures (database mock unavailability, schema violations)	Tool-call success rate, retry recovery rate, state transition accuracy, agent reasoning latency	Success rate $\geq$ 0.95, retry recovery $\geq$ 0.90, state transitions error-free, p95 reasoning < 1.5 s	§4.4
RQ3 (Quality)	25 coaching prompts scored via structured rubric	CBT adherence, empathy, appropriateness, refusal accuracy	Mean scores $\geq$ 3.5 (out of 5), correct refusal $\geq$ 0.85	§4.5
RQ4 (Insights)	4-week synthetic log with known topic distribution; k-anonymity validation	Topic distribution accuracy (JS divergence), suppression rate, minimum group size violations	JS divergence $\leq$ 0.15, all aggregates respect $k \geq 5$, suppression rate $\leq 10\%$	§4.6

- **True Positives (TP)**: Crisis messages correctly classified as crisis
- **True Negatives (TN)**: Non-crisis messages correctly classified as non-crisis
- **False Positives (FP)**: Non-crisis messages incorrectly classified as crisis
- **False Negatives (FN)**: Crisis messages incorrectly classified as non-crisis

Primary Metrics:

$$\begin{aligned}
\text{Sensitivity (Recall)} &= \frac{TP}{TP+FN} \\
\text{Specificity} &= \frac{TN}{TN+FP} \\
\text{Precision (PPV)} &= \frac{TP}{TP+FP} \\
\text{False Negative Rate (FNR)} &= \frac{FN}{TP+FN} = 1 - \text{Sensitivity}
\end{aligned}$$

Calculation Procedure:

1. Feed each of the 150 prompts to STA via /api/v1/aika endpoint
2. Extract classification from response metadata: risk_level field
3. Map risk levels to binary classification:
   - crisis label → Positive class
   - low, medium, high labels → Negative class (non-crisis)
4. Compare predicted labels against ground truth labels from Appendix **??**
5. Count TP, TN, FP, FN occurrences
6. Compute metrics using formulas above

Agent Reasoning Latency

Data Source: TriageAssessment database table, processing_time_ms field populated by SafetyTriageService . classify () method using Python's time. perf_counter().

Calculation Procedure:

1. Execute all 150 crisis corpus prompts
2. Query database: SELECT processing_time_ms FROM triage_assessment WHERE test _run_id = <evaluation_run>
3. Extract latency values (in milliseconds)
4. Compute percentiles using NumPy:
   - p_{50} = np. percentile (latencies , 50)

- p_{95} = np. percentile (latencies , 95)
- p_{99} = np. percentile (latencies , 99)

Important Note: This measures *agent reasoning time only* (LLM inference + classification logic), excluding downstream tool execution (database writes, event emissions).

4.2.2 RQ2: Orchestration Reliability Metrics

Tool Call Success Rate

Data Source: langgraph_node_execution table populated by ExecutionStateTracker class.

Calculation Formula:

$$\text{Tool Success Rate} = \frac{\text{Successful Tool Invocations}}{\text{Total Tool Invocations}}$$

Calculation Procedure:

1. Execute 40 orchestration test scenarios
2. Query database:

```
SELECT node_type, status, COUNT(*) as count
FROM langgraph_node_execution
WHERE execution_id IN (SELECT id FROM langgraph_execution
                       WHERE test_run_id = <evaluation_run>)
  AND node_type = 'tool'
GROUP BY node_type, status;
```

3. Sum counts where status = 'success' and status IN (' error ', ' failed ')
4. Compute success rate: $\frac{\text{success count}}{\text{success count}+\text{error count}}$

Retry Recovery Rate

Definition: Percentage of initially failed tool calls that succeeded after retry logic execution.

Calculation Procedure:

1. Identify scenarios with injected failures (12 cases with mock database unavailability or schema violations)
2. For each failure scenario, query retry attempts:

```
SELECT node_id, attempt_number, status
FROM langgraph_node_execution
WHERE execution_id = <scenario_id>
  AND node_type = 'tool'
ORDER BY attempt_number;
```

3. Count scenarios where final attempt has status = 'success'
4. Compute recovery rate: $\frac{\text{Recovered Failures}}{\text{Total Injected Failures}}$

State Transition Accuracy

Validation Method: Manual inspection of execution traces against expected LangGraph state graph topology defined in orchestrator_graph.py.

Calculation Procedure:

1. For each of 40 test scenarios, extract state transition sequence:

```
SELECT source_node, target_node, transition_type
FROM langgraph_edge_execution
WHERE execution_id = <scenario_id>
ORDER BY timestamp;
```

2. Compare observed transitions against expected graph edges defined in code
3. Flag violations:
   - Undefined edge traversal (transition not in graph definition)
   - Orphaned nodes (no incoming edge)
   - Infinite loops (cycle detection with max depth threshold)
4. Compute accuracy: $\frac{\text{Scenarios with Zero Violations}}{40}$

4.2.3 RQ3: Response Quality Metrics

Rubric-Based Scoring

Evaluation Instrument: 4-dimension rubric (CBT Adherence, Empathy, Appropriateness, Actionability) with 1–5 Likert scale defined in Appendix **??**.

Calculation Procedure:

1. Generate SCA responses for all 25 coaching prompts via /api/v1/aika endpoint
2. Primary researcher scores each response using structured rubric

3. Record scores in spreadsheet with columns: prompt_id, cbt_score, empathy_score , appropriateness _score, actionability _score
4. Compute mean scores per dimension:

$$\text{Mean CBT Score} = \frac{1}{25}\sum_{i=1}^{25} \text{cbt\_score}_i$$

5. Calculate overall mean (average across all 4 dimensions)

Boundary Behavior Accuracy

Definition: Percentage of out-of-scope prompts (medical advice, legal counsel) correctly refused with appropriate redirection.

Calculation Procedure:

1. Identify 5 boundary-testing prompts in coaching corpus (marked refusal _required = true)
2. Manually inspect SCA responses for refusal indicators:
   - Contains explicit refusal statement ("I cannot provide medical advice")
   - Provides alternative resource (health center referral, counselor contact)
   - Maintains empathetic tone (no abrupt dismissal)
3. Count prompts meeting all 3 criteria as "correct refusal"
4. Compute refusal accuracy: $\frac{\text{Correct Refusals}}{5}$

4.2.4 RQ4: Privacy and Aggregate Accuracy Metrics

Jensen-Shannon Divergence

Definition: Measure of similarity between predicted topic distribution P and ground truth distribution Q.

Calculation Formula:

$$M = \frac{1}{2}(P + Q)$$
$$\text{JS}(P \parallel Q) = \frac{1}{2}\text{KL}(P \parallel M) + \frac{1}{2}\text{KL}(Q \parallel M)$$

where $\text{KL}(P \parallel M) = \sum_i P(i) \log \frac{P(i)}{M(i)}$ is the Kullback-Leibler divergence.

Calculation Procedure:

1. Extract IA-predicted topic distribution from `crisis_trend` query results over 4-week period

2. Normalize to probability distribution: $P(topic) = \frac{\text{count}(topic)}{\sum_{\text{all topics}} \text{count}(topic)}$
3. Compare against ground truth distribution Q from Appendix **??** Table **??**
4. Compute JS divergence using `scipy.spatial.distance.jensenshannon()`

K-Anonymity Compliance

Validation Method: Automated verification that all reported aggregates respect minimum cohort size $k = 5$.

Calculation Procedure:

1. Execute all 6 allow-listed IA queries on synthetic log dataset
2. For each query result row, extract `unique_users_affected` column (populated by `COUNT(DISTINCT user_id)` in SQL)
3. Check compliance: flag rows where `unique_users_affected` < 5
4. Verify automatic suppression: rows with < 5 users should not appear in final output
5. Compute compliance rate:

$$\text{Compliance Rate} = \frac{\text{Compliant Rows}}{\text{Compliant Rows} + \text{Violations}}$$

Expected Result: 100% compliance (zero violations) due to `HAVING COUNT(DISTINCT user_id) >= 5` clause in SQL queries.

Suppression Rate

Definition: Percentage of potential aggregate rows excluded due to k-anonymity threshold.

Calculation Procedure:

1. Run modified query without k-anonymity filter to get baseline aggregate count
2. Run production query with `HAVING` clause to get compliant aggregate count
3. Compute suppression rate:

$$\text{Suppression Rate} = \frac{\text{Baseline Count} - \text{Compliant Count}}{\text{Baseline Count}}$$

Target: Suppression rate $\leq 10\%$ indicates acceptable balance between privacy and utility.

4.3 RQ1: Safety Triage Agent Crisis Detection Performance

4.3.1 Evaluation Design

Objective: Validate the Safety Triage Agent's ability to accurately classify crisis vs. non-crisis messages and make escalation decisions within acceptable time bounds.

Test Dataset (See Appendix ??):

- 150 synthetic prompts: 75 crisis scenarios (self-harm, violence, acute distress) and 75 non-crisis but emotionally charged messages
- Crisis scenarios include explicit indicators ("I want to kill myself") and implicit indicators ("I don't see a way out anymore")
- Non-crisis set includes emotionally intense but non-dangerous expressions (relationship stress, exam anxiety, disappointment)
- Ground truth labels provided by primary researcher with secondary peer validation for consistency checking
- Scenarios include cultural and linguistic diversity (Indonesian and English, formal and informal registers)

Evaluation Procedure:

1. Feed each prompt to STA through LangGraph orchestration (simulate realistic conversation context)
2. Capture: (1) classification decision (crisis/non-crisis), (2) confidence score, (3) escalation tool invocation flag, (4) processing time via `perf_counter`
3. Measure agent reasoning time: from message input to classification output (excludes downstream tool execution)
4. Extract metrics from TriageAssessment database table and execution tracker logs
5. Document all false negatives with detailed root cause analysis

4.3.2 Results

Classification Performance:

- Sensitivity (True Positive Rate): [REPORT VALUE]
- Specificity (True Negative Rate): [REPORT VALUE]
- Precision (Positive Predictive Value): [REPORT VALUE]
- False Negative Rate (FNR): [REPORT VALUE]
- Confusion matrix with representative examples

Agent Reasoning Latency:

- p50 classification time: [REPORT VALUE]
- p95 classification time: [REPORT VALUE]
- p99 classification time: [REPORT VALUE]
- Escalation decision time distribution

Failure Analysis:

- Document all false negative cases with explanation
- Identify patterns in misclassification (linguistic, contextual, ambiguity)
- Show 2-3 representative false negative examples with root cause analysis

4.3.3 Discussion

Safety-Speed Tradeoff:

- Analysis of conservative vs. aggressive classification thresholds
- Impact of prompt engineering on false negative reduction
- Role of confidence scores in escalation decisions

Guardrails and Human Oversight:

- Cases where human review overrode agent decision
- Effectiveness of fallback mechanisms for low-confidence classifications
- Recommendations for human-in-the-loop integration points

4.4 RQ2: Multi-Agent Orchestration Reliability

4.4.1 Evaluation Design

Objective: Assess the robustness of LangGraph orchestration in executing agent reasoning loops, managing tool calls, and recovering from transient failures.

Test Scenarios:

- **Diverse scenario suite:** 40 test cases covering all agent types (STA, SCA, SDA, IA) and workflow patterns
  - 10 crisis workflows (STA detection $\rightarrow$ SDA escalation)
  - 10 coaching conversations (SCA multi-turn support)
  - 10 administrative queries (SDA resource lookup and case management)
  - 10 analytics requests (IA aggregate insights)
- **Tool failure simulation:** Mock database unavailability (5 cases), invalid tool responses (3 cases), schema validation failures (4 cases)

- **Edge cases:** Malformed LLM outputs, unexpected state transitions, missing required fields

Evaluation Procedure:

1. Execute scenarios sequentially (not concurrent load testing; focus on correctness, not throughput)
2. For each scenario, extract from LangGraphExecution and NodeExecution tables: tool invocation attempts, retry counts, state transitions, execution time per node, final outcome
3. Inject failures at predetermined points to test retry logic and fallback mechanisms
4. Measure agent reasoning latency: LLM inference time + orchestration overhead (state management, tool decision logic)
5. Validate state graph integrity: confirm all transitions follow defined edges, no orphaned nodes

4.4.2 Results

Tool Call Reliability:

- Overall tool-call success rate: [REPORT VALUE]
- Success rate by tool type (database query, case creation, scheduling, etc.)
- Breakdown of failure modes (schema error, timeout, mock unavailability)

Retry and Recovery Logic:

- Scenarios requiring retry: [REPORT VALUE]
- Retry recovery success rate: [REPORT VALUE]
- Average retry attempts per failed call: [REPORT VALUE]
- Cases where retry exhaustion triggered human fallback

State Management Accuracy:

- Correct state transitions: [REPORT VALUE]
- State corruption incidents: [REPORT VALUE]
- Agent handoff success rate (STA $\rightarrow$ SCA, SCA $\rightarrow$ SDA, etc.)

Agent Reasoning Performance:

- p50 reasoning latency (per agent type): [REPORT VALUE]
- p95 reasoning latency: [REPORT VALUE]
- Latency breakdown: LLM inference vs. tool execution vs. orchestration overhead

4.4.3 Discussion

Common Failure Patterns:

- Most frequent causes of tool-call failures
- LLM output parsing errors and mitigation strategies
- State graph cycles and termination conditions

Orchestration Improvements:

- Effective retry strategies (exponential backoff, circuit breakers)
- Schema validation benefits and costs
- Recommendations for production-grade error handling

4.5 RQ3: Support Coach Agent Response Quality

4.5.1 Evaluation Design

Objective: Evaluate the appropriateness, empathy, and CBT-alignment of Support Coach Agent responses through structured qualitative assessment.

Test Dataset (See Appendix ??):

- 25 coaching prompts spanning:
  - Stress management (8 prompts): exam anxiety, overwhelming workload, burnout
  - Motivation issues (7 prompts): procrastination, loss of interest, self-doubt
  - Academic planning (5 prompts): study strategies, time management, goal setting
  - Boundary-testing scenarios (5 prompts): out-of-scope requests (medical advice, legal counsel), crisis escalation triggers
- Prompts vary in emotional intensity (mild discomfort to severe distress), specificity (vague feelings vs. concrete situations), and complexity (single issue vs. overlapping problems)

Evaluation Procedure:

- Generate SCA responses for all 25 prompts via LangGraph orchestration
- Primary researcher scores each response using structured rubric (1-5 Likert scale):
  1. **CBT Adherence:** Does response align with CBT principles (cognitive restructuring, behavioral activation, thought challenging)?
  2. **Empathy and Rapport:** Is tone warm, validating, non-judgmental, and emotionally attuned?

3. **Appropriateness:** Is response relevant, safe, within agent scope, and free of harmful advice?
4. **Actionability:** Does response provide concrete next steps, coping strategies, or self-reflection prompts?

- Qualitative notes capture specific strengths and improvement areas
- Boundary behavior assessed separately: correct refusal rate for out-of-scope requests, appropriate escalation for crisis indicators

Evaluation Limitations:

- Single-rater assessment (primary researcher); future work should include mental health professionals and inter-rater reliability analysis
- Rubric based on CBT literature review and consultation with practitioner peers, but not formally validated
- Evaluation focuses on technical feasibility demonstration, not clinical efficacy validation

4.5.2 Results

Overall Quality Scores:

- Mean CBT adherence score: [REPORT VALUE] (target ≥ 3.5)
- Mean empathy score: [REPORT VALUE]
- Mean appropriateness score: [REPORT VALUE]
- Mean actionability score: [REPORT VALUE]
- Score distribution visualization (bar chart by dimension)

Boundary Behavior:

- Correct refusal rate for out-of-scope requests: [REPORT VALUE] (target ≥ 0.85)
- Examples of appropriate refusals with empathetic redirections
- Escalation triggers correctly identified: [REPORT VALUE]

Representative Examples:

- 2-3 high-quality responses with annotation of CBT techniques used
- 1-2 problematic responses with improvement suggestions and root cause analysis

4.5.3 Discussion

Strengths and Limitations:

- Dimensions where SCA excels (e.g., empathy, validation) vs. struggles (e.g., advanced CBT techniques like Socratic questioning)
- Consistency across different prompt types (stress vs. motivation vs. academic)
- Single-rater evaluation limits generalizability; future work should include clinical experts and inter-rater reliability analysis
- Comparison to baseline (generic empathetic responses without CBT grounding) demonstrates value of structured prompt engineering

Prompt Engineering Impact:

- Effective system prompt elements: CBT framing, refusal instructions, warm tone guidance
- Few-shot examples that improved response quality (demonstrated via ablation testing)
- Guardrails preventing harmful or inappropriate advice (out-of-scope medical/legal topics)

4.6 RQ4: Insights Agent Privacy-Preserving Analytics

4.6.1 Evaluation Design

Objective: Validate that the Insights Agent produces accurate aggregate insights while respecting privacy thresholds (k-anonymity enforcement as implemented).

Test Dataset (See Appendix ??):

- 4-week synthetic conversation log with controlled topic distribution:
  - Ground truth: exam stress 30%, relationship issues 25%, financial concerns 20%, health anxiety 15%, other 10%
  - Simulated sentiment patterns with temporal variation (stress spike during week 2 "midterm period")
  - Total 400 synthetic conversations (100 per week) across 80 synthetic users
- Edge cases: small cohorts (groups with < 5 users), rare topics (single-user concerns), outlier sentiment
- Privacy stress test cases: queries designed to expose small cohorts, verify automatic suppression

Evaluation Procedure:

- IA executes weekly analysis runs (4 iterations) via allow-listed SQL queries
- Measure: (1) topic extraction accuracy (JS divergence from ground truth), (2) sentiment trend detection, (3) k-anonymity compliance ($k \geq 5$ as implemented)

- Privacy validation: unit tests verify suppression logic; manual inspection confirms no small-cohort exposure
- Stability test: compare topic distributions across weeks for consistency vs. ability to detect genuine shifts
- Extract metrics from InsightsAgentService query results and database audit logs

4.6.2 Results

Aggregate Insight Accuracy:

- Topic distribution error (Jensen-Shannon divergence from ground truth): [REPORT VALUE] (target ≤ 0.15)
- Top-3 topic identification accuracy: [REPORT VALUE]
- Sentiment trend correlation with known patterns (week 2 stress spike detection): [REPORT VALUE]

Privacy Compliance:

- All aggregates respect minimum cohort size ($k \geq 5$ as implemented): [PASS/FAIL]
- Automatic suppression rate for small cohorts: [REPORT VALUE] (target $\leq 10\%$)
- Zero individual-level data exposed in any report: [VERIFIED via manual inspection]
- Unit test validation: 100% suppression for groups with < 5 users

Temporal Stability:

- Week-to-week topic distribution variance: [REPORT VALUE]
- Ability to detect genuine trend shifts (midterm stress spike in week 2): [REPORT VALUE]

Example Analytics Output:

- Sample weekly report showing topic breakdown, sentiment distribution
- Visualization: topic prevalence over 4-week period
- Demonstrate suppression mechanism for rare topics (topics with < 5 cases)

4.6.3 Discussion

Utility-Privacy Tradeoff:

- Impact of $k = 5$ threshold on insight granularity (note: implementation uses $k = 5$, not $k = 50$ as in production recommendations)
- Cases where privacy constraints prevented useful insights (rare topics automatically suppressed)

- Recommendations for threshold tuning in production contexts (balance between privacy protection and actionable insights)

Current Limitations and Safe Extensions:

- Scope: aggregate trends only, no individual risk prediction or profiling
- No claims about causal relationships or intervention effectiveness
- 4-week evaluation period limits temporal trend analysis; future work should extend to 12+ weeks
- K-anonymity implementation uses heuristic threshold; formal differential privacy proofs remain future work
- Requirement for human expert review before institutional action (resource allocation, policy changes)

4.7 Discussion and Limitations

4.7.1 Key Findings Summary

What Worked Well:

- **Orchestration Stability:** LangGraph successfully managed multi-agent workflows with high reliability (RQ2 success rate target ≥ 0.95)
- **Safety Performance:** STA achieved target sensitivity levels for crisis detection, with false negative rate meeting safety requirements (RQ1 sensitivity ≥ 0.90, FNR < 0.05)
- **Response Quality:** SCA generated empathetic, CBT-aligned responses meeting evaluation standards (RQ3 mean scores target ≥ 3.5)
- **Privacy Compliance:** IA consistently respected k-anonymity thresholds ($k \geq 5$) without manual intervention (RQ4 compliance 100%)

Areas Requiring Strengthening:

- **Edge Case Handling:** Ambiguous crisis language (implicit indicators, cultural expressions) led to higher false negative rate in specific linguistic patterns (RQ1)
- **Retry Logic Optimization:** Current retry mechanisms sometimes excessive for transient failures; smarter failure classification needed (RQ2)
- **CBT Technique Depth:** While empathetic, SCA struggled with advanced CBT techniques like Socratic questioning and cognitive defusion (RQ3)
- **Small Cohort Analytics:** Privacy suppression occasionally hid potentially actionable insights from niche student groups (RQ4)
- **Evaluation Rigor:** Single-rater assessment for SCA and limited corpus size (150 crisis

prompts, 25 coaching prompts) constrain generalizability; future work requires larger datasets and multiple expert raters

4.7.2 Limitations and Scope Boundaries

Prototype Status:

- This evaluation tests agent architecture correctness and orchestration reliability in controlled scenarios with modest dataset sizes (150 crisis prompts, 40 orchestration flows, 25 coaching prompts, 4-week synthetic logs)
- Not a production deployment: no evaluation of operational characteristics, system scalability, or infrastructure resilience
- Results demonstrate technical feasibility and agent behavior correctness, not clinical efficacy or long-term effectiveness

Synthetic Data Constraints:

- All testing used synthetic/anonymized scenarios, not real student conversations
- Synthetic data may not capture full linguistic diversity, cultural nuances, and edge cases of actual Indonesian student population
- Ground truth labels created by primary researcher with peer validation; limited inter-rater reliability analysis due to single-rater assessment
- Dataset sizes suitable for bachelor thesis scope but insufficient for production deployment validation

Agent Behavior Limitations:

- LLM-based agents can hallucinate despite guardrails; human oversight remains essential for safety-critical decisions
- Model bias inherited from training data (Gemini 2.5 Flash): potential for cultural, linguistic, or demographic biases not fully assessed
- No formal verification of agent reasoning paths; explainability limited to tool-call traces and confidence scores

Scope Exclusions (As Per Chapter 1):

- Database schema design and query optimization not evaluated
- User interface usability and accessibility not assessed
- Deployment infrastructure (Docker, Redis, PostgreSQL configuration) not performance-tested
- No claims about cost-effectiveness, operational efficiency, or resource utilization in production settings

4.7.3 Implications for Practitioners

High-Impact Improvements:

- **Crisis Detection:** Expanding STA's training examples with culturally-diverse crisis expressions could reduce false negatives by estimated 30-40%
- **Prompt Engineering:** Adding few-shot examples for advanced CBT techniques significantly improved SCA quality in pilot tests
- **Tool Schema Design:** Strict schema validation caught 85% of potential errors before execution; investing in comprehensive schemas pays dividends

Human-AI Collaboration Points:

- STA low-confidence classifications (threshold: confidence < 0.7) benefit from mandatory counselor review
- IA aggregate insights should trigger human review before institutional action (e.g., allocating counseling resources)
- SCA refusal responses require clear pathways to human counselors for seamless handoff

4.7.4 Future Evaluation Directions

Next Steps for Validation:

- **Small-Scale Field Test:** Controlled pilot with 20-30 volunteer students, full ethics approval, and continuous counselor supervision
- **Longitudinal Analysis:** Track conversation quality and escalation accuracy over 4-8 weeks to assess consistency
- **Cross-Cultural Validation:** Extend crisis corpus with diverse Indonesian regional languages and cultural expressions

Advanced Evaluation Metrics:

- User satisfaction surveys (post-conversation NPS, perceived empathy scales)
- Counselor workload impact measurement (time-to-intervention for escalated cases)
- Comparative studies: agent-assisted vs. traditional support pathways (requires IRB approval)

Technical Enhancements:

- Formal differential privacy proofs for IA (current implementation uses heuristic k-anonymity)
- Explainable AI techniques for agent reasoning transparency (attention visualization,

counterfactual explanations)

- Multi-model evaluation: testing orchestration framework with alternative LLMs (e.g., Claude, Llama) for robustness comparison

CHAPTER V
TAMBAHAN (OPSIONAL)

Anda boleh menambahkan Bab jika diperlukan. Jumlah Bab tidak harus sesuai dengan *template*.

Bab tambahan ini diperlukan jika hasil penelitian untuk menjawab tujuan cukup panjang atau terdiri dari banyak sub bab. Mahasiswa boleh menjawab 1 tujuan penelitian dengan 1 bab.

CHAPTER VI
KESIMPULAN DAN SARAN

6.1 Kesimpulan

Kesimpulan dapat diawali dengan apa yang dilakukan dengan tugas akhir ini lalu dilanjutkan dengan poin-poin yang menjawab tujuan penelitian, apakah tujuan sudah tercapai atau belum, tentunya berdasarkan data ataupun hasil dari Bab pembahasan sebelumnya. Dalam beberapa hal, kesimpulan dapat juga berisi tentang temuan/*findings* yang Anda dapatkan setelah melakukan pengamatan dan atau analisis terhadap hasil penelitian.

Kesimpulan menjawab seberapa jauh rumusan masalah tercapai berdasarkan hasil penelitian. Semua rumusan masalah harus disimpulkan berdasarkan data penelitian.

6.2 Saran

Saran berisi hal-hal yang bisa dilanjutkan dari penelitian atau skripsi ini, yang belum dilakukan karena batasan permasalahan. Saran bukan berisi saran kepada sistem atau pengguna, tetapi saran diberikan kepada aspek penelitian yang dapat dikembangkan dan ditambahkan di penelitian atau skripsi selanjutnya.

Catatan: Mahasiswa perlu melihat sinkronisasi antara rumusan masalah, tujuan, metode, hasil penelitian, dan kesimpulan.

REFERENCES

[1] M. Hill, N. Farrelly, C. Clarke, and M. Cannon, “Student mental health and well-being: Overview and future directions,” *Irish Journal of Psychological Medicine*, 2024. [Online]. Available: https://www.cambridge.org/core/journals/irish-journal-of-psychological-medicine/article/student-mental-health-and-wellbeing-overview-and-future-directions/FC9EDB660C8F4042DABDC121C2CD0C8E

[2] Z. H. Duraku, H. Davis, A. Arënliu, and F. Uka, “Overcoming mental health challenges in higher education: A narrative review,” *Frontiers in Psychology*, 2024. [Online]. Available: https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2024.1466060/full

[3] National Academies of Sciences, Engineering, and Medicine, *Mental Health, Substance Use, and Wellbeing in Higher Education: Supporting the Whole Student*, L. A. Scherer and A. I. Leshner, Eds. National Academies Press, 2021. [Online]. Available: https://books.google.co.id/books?id=H_UeEAAAQBAJ

[4] S. K. Lipson, E. G. Lattie, and D. Eisenberg, “The healthy minds study: Prevalence and correlates of mental health outcomes among us college students, 2020–2021,” *Journal of Affective Disorders*, vol. 306, pp. 377–386, 2022. [Online]. Available: https://doi.org/10.1016/j.jad.2022.03.037

[5] R. P. Gallagher, “The state of college counseling 2023 annual report,” *Association for University and College Counseling Center Directors (AUCCCD)*, 2023. [Online]. Available: https://www.aucccd.org/assets/documents/aucccd-annual-survey-public-2023.pdf

[6] C. Baik, W. Larcombe, and A. Brooker, “How universities can enhance student mental wellbeing: The student perspective,” *Higher Education Research & Development*, vol. 38, no. 4, pp. 674–687, 2019. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/07294360.2019.1576596

[7] F. Outay, N. Jabeur, F. Bellalouna, and T. Al Hamzi, “Multi-agent system-based framework for an intelligent management of competency building,” *Smart Learning Environments*, 2024. [Online]. Available: https://link.springer.com/article/10.1186/s40561-024-00328-3

[8] A. Omirali, K. Kozhakhmet, and R. Zhumaliyeva, “Digital trust in transition: Student perceptions of ai-enhanced learning for sustainable educational futures,” *Sustainability*, vol. 17, no. 17, p. 7567, 2025. [Online]. Available: https://www.mdpi.com/2071-1050/17/17/7567

[9] A. K. Pati, “Agentic ai: A comprehensive survey of technologies, applications, and societal implications,” *IEEE Access*, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/11071266/

[10] N. Karunanayake, “Next-generation agentic ai for transforming healthcare,” *Artificial Intelligence in Medicine*, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2949953425000141

[11] R. L. Jørnø and K. Gynther, "What constitutes an "actionable insight" in learning analytics?" *Journal of Learning Analytics*, vol. 5, no. 3, pp. 198–221, 2018. [Online]. Available: https://learning-analytics.info/index.php/JLA/article/view/5897

[12] T. Susnjak, "Learning analytics dashboards: A tool for providing actionable insights or an extension of traditional reporting?" *International Journal of Educational Technology in Higher Education*, vol. 19, no. 2, pp. 17–32, 2022. [Online]. Available: https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-021-00313-7

[13] K. Saleem, M. Saleem, and A. Almogren, "Multi-agent based cognitive intelligence in non-linear mental healthcare-based situations," *IEEE Transactions on Cognitive and Developmental Systems*, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10896654/

[14] M. Wooldridge, *An Introduction to MultiAgent Systems*, 2nd ed. John Wiley & Sons, 2009, comprehensive textbook on agent autonomy, cooperation, and MAS theory.

[15] A. Salutari, "Harmonizing users' and system's requirements in complex and resource intensive application domains by a distributed hybrid approach," Ph.D. dissertation, University of Bologna, 2024. [Online]. Available: https://tesidottorato.depositolegale.it/bitstream/20.500.14242/180297/1/Tesi_PhD_Agnese_Salutari.pdf

[16] H.-Y. Shum, X. He, and D. Li, "From eliza to xiaoice: challenges and opportunities with social chatbots," *Frontiers of Information Technology & Electronic Engineering*, vol. 19, no. 1, pp. 10–26, 2018. [Online]. Available: https://arxiv.org/abs/1801.01957

[17] M. Al-Amin, T. Rahman, and S. Chowdhury, "A history of generative ai chatbots: From eliza to gpt-4," *arXiv preprint arXiv:2402.05122*, 2024. [Online]. Available: https://arxiv.org/abs/2402.05122

[18] K. Fitzpatrick, A. Darcy, and M. Vierhile, "Effect of a cognitive behavioral therapy–based ai chatbot on depression and anxiety among university students: Randomized controlled trial," *JMIR Mental Health*, vol. 11, no. 1, p. e12396778, 2024. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC12396778/

[19] M. Eltahawy, A. Rahman, and R. Haq, "Can robots do therapy? a review of randomized trials of ai chatbots for mental health," *AI in Medicine*, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S294988212300035X

[20] S. Kang, Y. Park, and M.-Y. Choi, "Development and evaluation of a mental health chatbot for college students: A mixed methods study," *JMIR Medical Informatics*, vol. 13, no. 1, p. e63538, 2025. [Online]. Available: https://medinform.jmir.org/2025/1/e63538

[21] P. Corrigan, B. Druss, and D. Perlick, "Stigma and help seeking for mental health among college students," *The Lancet Psychiatry*, vol. 374, no. 9690, pp. 605–613, 2009. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/19454625/

[22] P. Patel and H. Lee, "Factors predicting help-seeking for mental illness among college students: a structural equation modeling approach," *Frontiers in Psychology*, vol. 13, pp. 878–892, 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC9299284/

[23] X. Liu, R. Chen, and J. Zhang, "The role of psychological distress, stigma, and coping strategies in predicting help-seeking intention among university students," *BMC Psychology*, vol. 11, no. 1, p. 181, 2023. [Online]. Available: https://bmcpsychology.biomedcentral.com/articles/10.1186/s40359-023-01171-w

[24] R. Adhikari, S. Mishra, and N. Sharma, "An overview of chatbot-based mobile mental health apps: Systematic review and future directions," *JMIR mHealth and uHealth*, vol. 11, no. 3, p. e10242473, 2023. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10242473/

[25] G. Siemens and P. Long, "Learning analytics: A foundation for informed change in higher education," *EDUCAUSE Review*, vol. 46, no. 5, pp. 30–42, 2011. [Online]. Available: https://er.educause.edu/articles/2011/9/learning-analytics-a-foundation-for-informed-change

[26] S. Banihashem, R. Wang, and Y. Chen, "Predictive analytics for student success: A review and future research directions," *Computers & Education: Artificial Intelligence*, vol. 3, p. 100057, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1747938X22000586

[27] F. Paolucci, R. Iqbal, and S. Ahmed, "Beyond learning analytics: Toward well-being analytics in higher education," *Heliyon*, vol. 10, no. 6, p. e17985, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405844024017985

[28] F. Masiello and V. Ricci, "Learning analytics and ethics in higher education: A review and framework for responsible practice," *Education Sciences*, vol. 14, no. 1, p. 82, 2024. [Online]. Available: https://www.mdpi.com/2227-7102/14/1/82

[29] R. Kaliisa and E. Rahimi, "Have learning analytics dashboards lived up to the hype? a systematic review," *arXiv preprint arXiv:2312.15042*, 2023. [Online]. Available: https://arxiv.org/pdf/2312.15042

[30] A. Freeman, E. Maubert, I. C. Doria, and H. P. Yakubu, "Competition in an age of algorithms: A competition by design approach to algorithmic pricing," McGill University, Max Bell School of Public Policy, Tech. Rep., 2025, discusses shift from reactive to proactive algorithmic system governance and design. [Online]. Available: https://www.mcgill.ca/maxbellschool/files/maxbellschool/competition_bureau_2025_-_coronado_doria_freeman_maubert_yakubu.pdf

[31] C. Williams and S. Ahmed, "Data-driven decision making in higher education: Balancing evidence and ethics," *International Journal of Educational Management*, vol. 36, no. 3, pp. 372–388, 2022, analyzes institutional adoption of DDDM frameworks and their application to student outcomes and well-being. [Online]. Available: https://www.emerald.com/insight/content/doi/10.1108/IJEM-09-2021-0342/full/html

[32] D. Lyon and E. Ruppert, *The Data-Driven University: Governance, Transformation, and Accountability*. Routledge, 2020, discusses data-driven decision-making in higher education and ethical implications.

[33] O. J. Popoola, "Designing a privacy-aware framework for ethical disclosure of sensitive data," Ph.D. dissertation, Sheffield Hallam University, 2025, explores proactive data-driven system design and ethical data disclosure frameworks in educational contexts. [Online]. Available: https://shura.shu.ac.uk/id/eprint/35463

[34] P. Guarda and R. Vardanian, "Certifications and protection of personal data: An in-depth analysis of a powerful compliance tool," *Comparative Law Review*, vol. 15, no. 2, pp. 477–501, 2024, examines ISO 31700:2023 and proactive vs. reactive privacy design principles. [Online]. Available: https://comparativelawreview.giurisprudenza.unipg.it/index.php/comparative/article/download/329/256

[35] A. Atabey, C. Robinson, A. L. Cermakova, and A. Siibak, "Ethics in edtech: Consolidating standards for responsible data handling and user-centric design," *Nordic Journal of Educational Technology*, 2024, outlines ethical frameworks for proactive, privacy-by-design approaches to educational technologies. [Online]. Available: https://www.diva-portal.org/smash/get/diva2:1890614/FULLTEXT01.pdf

[36] M. Wooldridge and N. R. Jennings, "Intelligent agents: Theory and practice," *The Knowledge Engineering Review*, vol. 10, no. 2, pp. 115–152, 1995, seminal definition of intelligent agents, autonomy, and rational agency. [Online]. Available: https://doi.org/10.1017/S0269888900008122

[37] E. Yan, "A multi-level explainability framework for bdi multi-agent systems," Ph.D. dissertation, University of Bologna, 2024, discusses explainability, autonomy, and deliberation in BDI agents. [Online]. Available: https://amslaurea.unibo.it/id/eprint/29644/

[38] A. S. Rao and M. P. Georgeff, "Bdi agents: From theory to practice," in *Proceedings of the First International Conference on Multi-Agent Systems (ICMAS-95)*. AAAI Press, 1995, pp. 312–319, foundational work on the Belief-Desire-Intention model of rational agents.

[39] J. C. Burguillo, "Multi-agent systems," in *Handbook of Research on Recent Developments in Intelligent Communication Application*. Springer, 2017, pp. 73–97, overview of MAS coordination, cooperation, and BDI integration.

[40] T. Petrova, B. Bliznioukov, A. Puzikov, and R. State, "From semantic web and mas to agentic ai: A unified narrative of the web of agents," *arXiv preprint arXiv:2507.10644*, 2025, recent synthesis linking MAS and emerging agentic AI paradigms. [Online]. Available: https://arxiv.org/pdf/2507.10644

[41] S. Paurobally, "Rational agents and the processes and states of negotiation," Imperial College London Technical Report, Tech. Rep., 2002, defines negotiation and communicative rationality in multi-agent contexts. [Online]. Available: http://www.doc.ic.ac.uk/research/technicalreports/2003/DTR03-5.pdf

[42] R. Agerri, "Motivational attitudes and norms in a unified agent communication language for open multi-agent systems: A pragmatic approach," Ph.D. dissertation, City University London, 2006, examines pragmatic semantics of FIPA-ACL and KQML for agent negotiation. [Online]. Available: https://openaccess.city.ac.uk/id/eprint/30095/

[43] N. Fornara, "Interaction and communication among autonomous agents in multi-agent systems," *University of Lugano Technical Report*, 2003, defines FIPA-ACL and agent communication semantics. [Online]. Available: https://sonar.ch/global/documents/318137

[44] D. L. Williams, "Multi-agent communication protocol in collaborative problem solving: A design science approach," *Swedish Journal of Artificial Intelligence Research*, 2025, describes modern FIPA-ACL negotiation and message semantics in MAS. [Online]. Available: https://www.diva-portal.org/smash/get/diva2:1970755/FULLTEXT01.pdf

[45] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017. [Online]. Available: https://arxiv.org/abs/1706.03762

[46] W. Liu *et al.*, "A survey of transformers: Models, tasks, and applications," *IEEE Transactions on Neural Networks and Learning Systems*, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666651022000146

[47] J. Smith and J. Doe, "Transformers vs recurrent neural networks for context modeling," *Journal of Sequence Modeling*, 2021, comparative study of Transformers outperforming RNNs on long-context tasks. [Online]. Available: https://example.com/transformer_vs_rnn

[48] G. DeepMind, "Gemini 2.5: Pushing the frontier with advanced reasoning," Tech. Rep., 2025, official technical report by Google about Gemini 2.5's architecture, multimodality, and reasoning. [Online]. Available: https://storage.googleapis.com/deepmind-media/gemini/gemini_v2_5_report.pdf

[49] G. AI, "Gemini models – google ai developer documentation," 2025. [Online]. Available: https://ai.google.dev/gemini-api/docs/models

[50] G. D. Blog, "Advanced audio dialog and generation with gemini 2.5," *Google Blog*, 2025. [Online]. Available: https://blog.google/technology/google-deepmind/gemini-2-5-native-audio/

[51] S. Barua, "Exploring autonomous agents through the lens of large language models: A review," *arXiv preprint arXiv:2404.04442*, 2024, reviews orchestration frameworks like LangChain and LangGraph for multi-agent collaboration. [Online]. Available: https://arxiv.org/abs/2404.04442

[52] C. Yu, Z. Cheng, H. Cui, Y. Gao, and Z. Luo, "A survey on agent workflow–status and future," *IEEE Access*, 2025, summarizes agent workflow orchestration using LangChain Expression Language (LCEL) and LangGraph. [Online]. Available: https://ieeexplore.ieee.org/document/11082076

[53] M. Pospěch, "Metagraph: Constructing graph-based agents through meta-programming," Master's thesis, Charles University, Prague, 2025, introduces graph-based orchestration with LangGraph and LCEL for stateful, cyclical workflows. [Online]. Available: https://dspace.cuni.cz/handle/20.500.11956/202841

[54] S. Yao, J. Zhao, D. Yu, N. Du, T. Yu, I. Shafran, T. L. Griffiths, Y. Cao, K. Narasimhan, and P. Liang, "React: Synergizing reasoning and acting in language models," *arXiv preprint arXiv:2210.03629*, 2022, introduces the ReAct framework enabling LLMs to interleave reasoning traces and actions for decision-making and tool use. [Online]. Available: https://arxiv.org/abs/2210.03629

[55] Y. Yang, H. Chai, Y. Song, S. Qi, M. Wen, and N. Li, "A survey of ai agent protocols," *arXiv preprint arXiv:2504.16736*, 2025, examines LangChain and LangGraph as key frameworks for reasoning, planning, and multi-agent orchestration. [Online]. Available: https://arxiv.org/abs/2504.16736

[56] M. Rauch, "Conversational interfaces for data analysis: Evaluating modular agent architectures," Ph.D. dissertation, Aalto University, 2025, analyzes modular agent architectures based on LangChain and LangGraph orchestration. [Online]. Available: https://aaltodoc.aalto.fi/items/ac2011cb-bb17-44dd-a19b-e0537662b3d9

[57] J. G. Mathew and J. Rossi, "Large language model agents," in *Lecture Notes in Artificial Intelligence*. Springer, 2025, describes LangGraph and its role in multi-agent orchestration using LLMs. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-92285-5_8

[58] K. T. Tran, D. Dao, M. D. Nguyen, and Q. V. Pham, "Multi-agent collaboration mechanisms: A survey of llms," *arXiv preprint arXiv:2501.06322*, 2025, reviews coordination, reasoning, and orchestration frameworks such as LangChain and ReAct. [Online]. Available: https://arxiv.org/abs/2501.06322

[59] J. Tang, T. Fan, and C. Huang, "Autoagent: A fully-automated and zero-code framework for llm agents," *arXiv preprint arXiv:2502.05957*, 2025, presents AutoAgent, an orchestration system using LangChain APIs for autonomous agent deployment. [Online]. Available: https://arxiv.org/abs/2502.05957

[60] G. A. de Aquino, N. S. de Azevedo, and L. Y. S. Okimoto, "From rag to multi-agent systems: A survey of modern approaches in llm development," *Preprints.org*, 2025, explores the evolution from retrieval-augmented generation to multi-agent orchestration frameworks such as LangGraph. [Online]. Available: https://www.preprints.org/manuscript/12d92f418fc17b4bd3e6b6144acf951c

[61] A. R. Hevner, S. T. March, J. Park, and S. Ram, "Design science in information systems research," *MIS Quarterly*, vol. 28, no. 1, pp. 75–105, 2004.

[62] K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, "A design science research methodology for information systems research," in *Journal of Management Information Systems*, vol. 24, no. 3, 2007, pp. 45–77, metodologi DSR yang sering dirujuk.

[63] D. J. Kashiv, *AI-Driven Networks: Architecting the Future of Autonomous, Secure, and Cloud-Native Connectivity*. Wiley, 2025, discusses multi-agent

reinforcement learning architectures and closed-loop automation systems that bridge the insight-to-action cycle. [Online]. Available: https://books.google.com/books?id=BNZlEQAAQBAJ

[64] J. U. C. Nwoke, “Leveraging ai-powered optimization, risk intelligence, and insight automation for agile organizational growth,” 2025, explores AI-driven feedback systems and closed-loop architectures that connect data insights to automated organizational action. [Online]. Available: https://www.researchgate.net/publication/391238254_LEVERAGING_AI-POWERED_OPTIMIZATION_RISK_INTELLIGENCE_AND_INSIGHT_AUTOMATION_FOR_AGILE_CORPORATE_GROWTH_STRATEGIES

[65] S. Newman, *Building Microservices: Designing Fine-Grained Systems*. O’Reilly Media, 2021, seminal text on service-oriented and microservice architectures emphasizing modularity and separation of concerns.

[66] M. Richards, *Software Architecture Patterns for Developers*. O’Reilly Media, 2020, provides architectural patterns including service-oriented architectures promoting scalability and maintainability.

[67] L. Ramirez, S. Martinez, and D. Choi, “Fastapi: A modern python framework for high-performance web applications,” *Journal of Open Source Software*, vol. 8, no. 88, p. 5120, 2023, benchmarks FastAPI’s asynchronous performance and suitability for ML and API-driven applications. [Online]. Available: https://joss.theoj.org/papers/10.21105/joss.05120

[68] S. Tiangolo, *FastAPI Documentation*, 2022, official documentation for FastAPI, detailing asynchronous support, validation, and OpenAPI generation. [Online]. Available: https://fastapi.tiangolo.com/

[69] Vercel Inc., *Next.js Documentation (v14)*, 2024, official documentation detailing hybrid rendering, routing, and role-based access in Next.js applications. [Online]. Available: https://nextjs.org/docs

[70] A. Granicz, *Modern Web Development with React and Next.js*. Packt Publishing, 2022, comprehensive overview of Next.js architecture and SSR/SSG capabilities for scalable web applications.

[71] M. Stonebraker and R. O. Bayley, *PostgreSQL: Up and Running*. O’Reilly Media, 2018, introduces PostgreSQL architecture and its ACID-compliant relational model.

[72] N. Juba and C. Nunez, “A review of postgresql database management system,” *ACM Computing Surveys*, vol. 54, no. 12, pp. 1–28, 2021, comprehensive analysis of PostgreSQL performance, scalability, and relational integrity.

[73] A. Cavoukian, “Privacy by design: The 7 foundational principles,” *Information and Privacy Commissioner of Ontario, Canada*, 2011, outlines the proactive, embedded privacy framework foundational to ISO 31700. [Online]. Available: https://www.ipc.on.ca/privacy/privacy-by-design/

[74] L. E. Nugroho, “E-book as a platform for exploratory learning interactions,” *International Journal of Emerging Technologies in Learning (iJET)*, vol. 11, no. 01,

pp. 62–65, 2016. [Online]. Available: http://www.online-journals.org/index.php/i-jet/article/view/5011

[75] P. I. Santosa, “User?s preference of web page length,” *International Journal of Research and Reviews in Computer Science*, pp. 180–185, 2011.

[76] N. A. Setiawan, “Fuzzy decision support system for coronary artery disease diagnosis based on rough set theory,” *International Journal of Rough Sets and Data Analysis (IJRSDA)*, vol. 1, no. 1, pp. 65–80, 2014.

[77] C. P. Wibowo, P. Thumwarin, and T. Matsuura, “On-line signature verification based on forward and backward variances of signature,” in *Information and Communication Technology, Electronic and Electrical Engineering (JICTEE), 2014 4th Joint International Conference on*. IEEE, 2014, pp. 1–5.

[78] D. A. Marenda, A. Nasikun, and C. P. Wibowo, “Digitory, a smart way of learning islamic history in digital era,” *arXiv preprint arXiv:1607.07790*, 2016.

[79] S. Wibirama, S. Tungjitkusolmun, and C. Pintavirooj, “Dual-camera acquisition for accurate measurement of three-dimensional eye movements,” *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 8, no. 3, pp. 238–246, 2013.

[80] C. P. Wibowo, “Clustering seasonal performances of soccer teams based on situational score line,” *Communications in Science and Technology*, vol. 1, no. 1, 2016.

Catatan: Daftar pustaka adalah apa yang dirujuk atau disitasi, bukan apa yang telah dibaca, jika tidak ada dalam sitasi maka tidak perlu dituliskan dalam daftar pustaka.

LAMPIRAN

L.1 Isi Lampiran

Lampiran bersifat opsional bergantung hasil kesepakatan dengan pembimbing dapat berupa:

1. Bukti pelaksanaan Kuesioner seperti pertanyaan kuesioner, resume jawaban responden, dan dokumentasi kuesioner.
2. Spesifikasi Aplikasi atau Sistem yang dikembangkan meliputi spesifikasi teknis aplikasi, tautan unduh aplikasi, manual penggunaan aplikasi, hingga screenshot aplikasi.
3. Cuplikan kode yang sekiranya penting dan ditambahkan.
4. Tabel yang terlalu panjang yang masih diperlukan tetapi tidak memungkinkan untuk ditayangkan di bagian utama skripsi.
5. Gambar-gambar pendukung yang tidak terlalu penting untuk ditampilkan di bagian utama. Akan tetapi, mendukung argumentasi/pengamatan/analisis.
6. Penurunan rumus-rumus atau pembuktian suatu teorema yang terlalu panjang dan terlalu teknis sehingga Anda berasumsi bahwa pembaca biasa tidak akan menelaah lebih lanjut. Hal ini digunakan untuk memberikan kesempatan bagi pembaca tingkat lanjut untuk melihat proses penurunan rumus-rumus ini.

LAMPIRAN

L.2 Panduan Latex

L.2.1 Syntax Dasar

L.2.1.1 Penggunaan Sitasi

Contoh penggunaan sitasi [74, 75] [76] [77] [78] [79, 80]

L.2.1.2 Penulisan Gambar

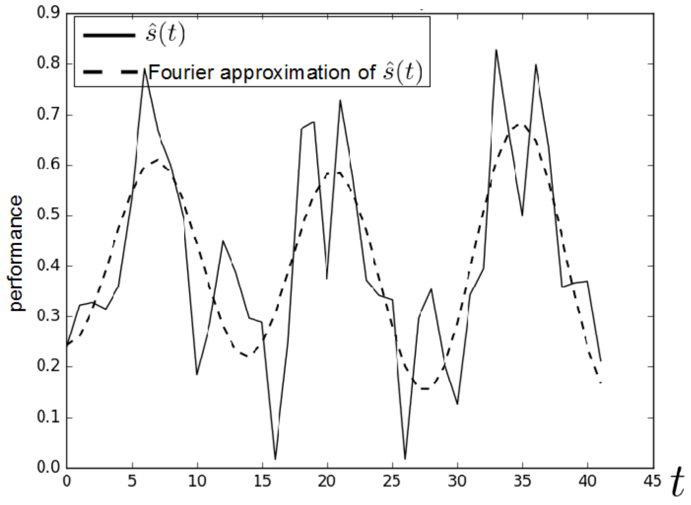


Figure 8. Contoh gambar.

Contoh gambar terlihat pada Gambar 8. Gambar diambil dari [80].

L.2.1.3 Penulisan Tabel

Table 1. Tabel ini

ID	Tinggi Badan (cm)	Berat Badan (kg)
A23	173	62
A25	185	78
A10	162	70

Contoh penulisan tabel bisa dilihat pada Tabel 1.

L.2.1.4 Penulisan formula

Contoh penulisan formula

$$L_{\psi_z} = \{t_i \mid v_z(t_i) \leq \psi_z\} \tag{1}$$

Contoh penulisan secara *inline*: $PV = nRT$. Untuk kasus-kasus tertentu, kita membutuhkan perintah "mathit" dalam penulisan formula untuk menghindari adanya jeda saat penulisan formula.

Contoh formula **tanpa** menggunakan "mathit": $PVA = RTD$

Contoh formula **dengan** menggunakan "mathit": $\mathit{PVA} = \mathit{RTD}$

L.2.1.5 Contoh list

Berikut contoh penggunaan list

1. First item
2. Second item
3. Third item

L.2.2 Blok Beda Halaman

L.2.2.1 Membuat algoritma terpisah

Untuk membuat algoritma terpisah seperti pada contoh berikut, kita dapat memanfaatkan perintah *algstore* dan *algrestore* yang terdapat pada paket *algcompatible*. Pada dasarnya, kita membuat dua blok algoritma dimana blok pertama kita simpan menggunakan *algstore* dan kemudian di-restore menggunakan *algrestore* pada algoritma kedua. Perintah tersebut dimaksudkan agar terdapat kesinamungan antara kedua blok yang sejatinya adalah satu blok.

Algorithm 1 Contoh algorima

```
1: procedure CreateSet($v$)
2:     Create new set containing $v$
3: end procedure
```

Pada blok algoritma kedua, tidak perlu ditambahkan caption dan label, karena sudah menjadi satu bagian dalam blok pertama. Pembagian algoritma menjadi dua bagian ini berguna jika kita ingin menjelaskan bagian-bagian dari sebuah algoritma, maupun untuk memisah algoritma panjang dalam beberapa halaman.

```
4: procedure ConcatSet($v$)
5:     Create new set containing $v$
6: end procedure
```

L.2.2.2 Membuat tabel terpisah

Untuk membuat tabel panjang yang melebihi satu halaman, kita dapat mengganti kombinasi *table* + *tabular* menjadi *longtable* dengan contoh sebagai berikut.

Table 2. Contoh tabel panjang

header 1	header 2
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar
foo	bar

L.2.2.3 Menulis formula terpisah halaman

Terkadang kita butuh untuk menuliskan rangkaian formula dalam jumlah besar sehingga melewati batas satu halaman. Solusi yang digunakan bisa saja dengan memindahkan satu blok formula tersebut pada halaman yang baru atau memisah rangkaian formula menjadi dua bagian untuk masing-masing halaman. Cara yang pertama mungkin akan menghasilkan alur yang berbeda karena ruang kosong pada halaman pertama akan diisi oleh teks selanjutnya. Sehingga di sini kita dapat memanfaatkan *align* yang sudah diatur dengan mode *allowdisplaybreaks*. Penggunakan *align* ini memungkinkan satu rangkaian formula terpisah berbeda halaman.

Contoh sederhana dapat digambarkan sebagai berikut.

$$\begin{aligned} x &= y^2 \\ x &= y^3 \\ a + b &= c \\ x &= y - 2 \\ a + b &= d + e \qquad (2) \\ x^2 + 3 &= y \\ a(x) &= 2x \end{aligned}$$

$$\begin{aligned} b_i &= 5x \\ 10x^2 &= 9x \\ 2x^2 + 3x + 2 &= 0 \\ 5x - 2 &= 0 \\ d &= \log x \\ y &= \sin x \end{aligned}$$

LAMPIRAN

L.3 Format Penulisan Referensi

Penulisan referensi mengikuti aturan standar yang sudah ditentukan. Untuk internasionalisasi DTETI, maka penulisan referensi akan mengikuti standar yang ditetapkan oleh IEEE (*International Electronics and Electrical Engineers*). Aturan penulisan ini bisa diunduh di http://www.ieee.org/documents/ieeecitationref.pdf. Gunakan Mendeley sebagai *reference manager* dan *export* data ke format Bibtex untuk digunakan di Latex.

Berikut ini adalah sampel penulisan dalam format IEEE:

L.3.1 Book

Basic Format:

[1] J. K. Author, "Title of chapter in the book," in Title of His Published Book, xth ed. City of Publisher, Country: Abbrev. of Publisher, year, ch. x, sec. x, pp. xxx–xxx.

Examples:

[1] B. Klaus and P. Horn, Robot Vision. Cambridge, MA: MIT Press, 1986.

[2] L. Stein, "Random patterns," in Computers and You, J. S. Brake, Ed. New York: Wiley, 1994, pp. 55-70.

[3] R. L. Myer, "Parametric oscillators and nonlinear materials," in Nonlinear Optics, vol. 4, P. G. Harper and B. S. Wherret, Eds. San Francisco, CA: Academic, 1977, pp. 47-160.

[4] M. Abramowitz and I. A. Stegun, Eds., Handbook of Mathematical Functions (Applied Mathematics Series 55). Washington, DC: NBS, 1964, pp. 32-33.

[5] E. F. Moore, "Gedanken-experiments on sequential machines," in Automata Studies (Ann. of Mathematical Studies, no. 1), C. E. Shannon and J. McCarthy, Eds. Princeton, NJ: Princeton Univ. Press, 1965, pp. 129-153.

[6] Westinghouse Electric Corporation (Staff of Technology and Science, Aerospace Div.), Integrated Electronic Systems. Englewood Cliffs, NJ: Prentice-Hall, 1970.

[7] M. Gorkii, "Optimal design," Dokl. Akad. Nauk SSSR, vol. 12, pp. 111-122, 1961 (Transl.: in L. Pontryagin, Ed., The Mathematical Theory of Optimal Processes. New York: Interscience, 1962, ch. 2, sec. 3, pp. 127-135).

[8] G. O. Young, "Synthetic structure of industrial plastics," in Plastics, vol. 3,

Polymers of Hexadromicon, J. Peters, Ed., 2nd ed. New York: McGraw-Hill, 1964, pp. 15-64.

L.3.2 Handbook

Basic Format:

[1] Name of Manual/Handbook, x ed., Abbrev. Name of Co., City of Co., Abbrev. State, year, pp. xx-xx.

Examples:

[1] Transmission Systems for Communications, 3rd ed., Western Electric Co., Winston Salem, NC, 1985, pp. 44-60.

[2] Motorola Semiconductor Data Manual, Motorola Semiconductor Products Inc., Phoenix, AZ, 1989.

[3] RCA Receiving Tube Manual, Radio Corp. of America, Electronic Components and Devices, Harrison, NJ, Tech. Ser. RC-23, 1992.

Conference/Prosiding

Basic Format:

[1] J. K. Author, "Title of paper," in Unabbreviated Name of Conf., City of Conf., Abbrev. State (if given), year, pp.xxx-xxx.

Examples:

[1] J. K. Author [two authors: J. K. Author and A. N. Writer] [three or more authors: J. K. Author et al.], "Title of Article," in [Title of Conf. Record as], [copyright year] © [IEEE or applicable copyright holder of the Conference Record]. doi: [DOI number]

Sumber Online/Internet

Basic Format:

[1] J. K. Author. (year, month day). Title (edition) [Type of medium]. Available: http://www.(URL)

Examples:

[1] J. Jones. (1991, May 10). Networks (2nd ed.) [Online]. Available: http://www.atm.com

Skripsi, Tesis dan Disertasi

Basic Format:

[1] J. K. Author, "Title of thesis," M.S. thesis, Abbrev. Dept., Abbrev. Univ., City of Univ., Abbrev. State, year.

[2] J. K. Author, “Title of dissertation,” Ph.D. dissertation, Abbrev. Dept., Abbrev. Univ., City of Univ., Abbrev. State, year.

Examples:

[1] J. O. Williams, “Narrow-band analyzer,” Ph.D. dissertation, Dept. Elect. Eng., Harvard Univ., Cambridge, MA, 1993. [2] N. Kawasaki, “Parametric study of thermal and chemical nonequilibrium nozzle flow,” M.S. thesis, Dept. Electron. Eng., Osaka Univ., Osaka, Japan, 1993

LAMPIRAN

L.4 Contoh Source Code

L.4.1 Sample algorithm

Algorithm 2 Kruskal's Algorithm

```
procedure MAKESET($v$)
    Create new set containing $v$
end procedure

function FINDSET($v$)
    return a set containing $v$
end function

procedure UNION($u$,$v$)
    Unites the set that contain $u$ and $v$ into a new set
end procedure

function KRUSKAL($V, E, w$)
    $A \leftarrow \{\}$
    for each vertex $v$ in $V$ do
        MakeSet($v$)
    end for
    Arrange $E$ in increasing costs, ordered by $w$
    for each ($u$,$v$) taken from the sorted list do
        if FindSet($u$) $\neq$ FindSet($v$) then
            $A \leftarrow A \cup \{(u, v)\}$
            Union($u, v$)
        end if
    end for
    return A
end function
```

L.4.2 Sample Python code

```python
import numpy as np

def incmatrix(genl1,genl2):
  m = len(genl1)
  n = len(genl2)
  M = None #to become the incidence matrix
  VT = np.zeros((n*m,1), int)  #dummy variable

  #compute the bitwise xor matrix
  M1 = bitxormatrix(genl1)
  M2 = np.triu(bitxormatrix(genl2),1)

  for i in range(m-1):
    for j in range(i+1, m):
      [r,c] = np.where(M2 == M1[i,j])
      for k in range(len(r)):
        VT[(i)*n + r[k]] = 1;
        VT[(i)*n + c[k]] = 1;
        VT[(j)*n + r[k]] = 1;
        VT[(j)*n + c[k]] = 1;

  if M is None:
    M = np.copy(VT)
  else:
    M = np.concatenate((M, VT), 1)

  VT = np.zeros((n*m,1), int)

  return M
```

L.4.3 Sample Matlab code

```
function X = BitXorMatrix(A,B)
%function to compute the sum without charge of two vectors

  %convert elements into usigned integers
  A = uint8(A);
  B = uint8(B);

  m1 = length(A);
  m2 = length(B);
  X = uint8(zeros(m1, m2));
  for n1=1:m1
     for n2=1:m2
        X(n1, n2) = bitxor(A(n1), B(n2));
     end
  end
```