Simulating Learner Communities: A BDI-Based Virtual Student Community

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***Abstract*—The adoption of learning management systems (LMS) has generated large volumes of data, enabling monitoring, assessment, and prediction of learning outcomes to improve platform quality. Traditional LMS evaluation requires repeated, resource-intensive experiments with active learner communities. To overcome these constraints, we propose a Virtual Student Community (VSC) built on a Belief–Desire–Intention (BDI) multi-agent model and the Myers-Briggs Type Indicator (MBTI). The VSC reduces evaluation costs, improves interaction quality, and allows configurable, fine-grained monitoring. In this article, we present an overview of the VSC's architecture, main components, and preliminary evaluation results.**

***Index Terms*—Distributed learning environments, multi-agent system, BDI model, Myers-Briggs Type Indicator (MBTI), simulations, distance education and online learning.**

I. Introduction

E-learning is a distance education that uses digital platforms and resources to provide educational content to students, using digital platforms and resources to distribute educational information over large geographical areas [1]. Pedagogically, E-learning is student cantered and collaborative learning. It serves learning and teaching procedure through all electronic forms [2]. E-learning platforms produce a vast amount of data, capturing logs and digital traces of user interactions, both among participants (such as communication and collaboration) and with the system itself (such as logins, content viewing, and file submissions). A useful data that learning analytics relies on.

Online learning analytics has emerged as a critical tool to derive insights from student learning behaviors, offering flexible educational access and promoting lifelong learning [3]. It focuses on using computational methods to analyze data generated during the learning process, with the goal of better understanding and enhancing learning outcomes [4].

Several studies have leveraged behavioral and interaction data to enhance the analysis, evaluation, and optimization of learning processes in digital education environments.

Vieira, Goldstein, Purzer, and Magana from Purdue University [5] proposed and evaluated a model designed to analyze student interactions within a computer-aided design (CAD) environment. Their work aimed to identify and characterize the strategies students employ while conducting design experiments. In the first phase of their study, clickstream data from 51 middle school students engaged in a "net-zero energy house" design project were collected and analyzed. The quantitative analysis of clickstream data was then compared to a qualitative assessment based on open-ended posttests. This combination provided deeper insight into the relationship between interaction patterns and problem-solving strategies, demonstrating the potential of behavioral data to reveal learning dynamics beyond traditional evaluation methods.

In another study, a multi-agent approach was proposed to support learning activities within a Virtual Learning Environment (VLE) [6]. This system was designed to assist teachers in monitoring and managing collaborative learning processes. By estimating a sociological or behavioral profile for each learner, the agents could provide adaptive support and feedback, thereby facilitating more personalized and efficient instruction. Such agent-based frameworks highlight the value of modeling individual and group behaviors for improving coordination and engagement in online education.

A third example is presented in "A Case Study of Usability Testing on an Asynchronous e-Learning Platform" [7]. The authors evaluated a non-degree e-learning platform using both performance metrics and user perception analyses to assess efficiency, effectiveness, and satisfaction. Efficiency and effectiveness were measured through task completion time and success rate, while satisfaction was assessed through participant questionnaires and qualitative feedback. This mixed-methods approach provided a comprehensive understanding of user experience, reinforcing the importance of combining behavioral data with subjective evaluations for a holistic assessment of e-learning platforms.

Collectively, these works demonstrate the growing interest in using behavioral, interactional, and usability data to model learner behavior, evaluate system performance, and enhance virtual learning environments. They also illustrate complementary methodologies—ranging from clickstream analytics and multi-agent modeling to usability testing—that together contribute to a more data-driven understanding of learning processes in digital contexts.

In all these experiments and studies, a large number of learners and multiple tutors have been involved to operate an E-learning platform effectively and to generate sufficient data for analysis. To organize a series of evaluation tests for an e-learning platform, structured organizational procedures should be implemented to ensure participant availability, engagement,

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and data reliability. These include clearly defined recruitment criteria aligned with target users, formal registration and scheduling mechanisms, and flexible testing timelines. Motivation can be enhanced through incentives such as certificates, academic credit, or early platform access. Orientation sessions should be provided to reduce technical misunderstandings, while reminder systems and progress tracking can support commitment. Additionally, technical assistance, standardized data collection protocols, and strict ethical and data protection measures are essential to ensure methodological rigor and participant trust.

Main contributions of this work are:

- A novel Virtual Student Community (VSC): Unlike traditional methods relying on human participation, we propose a simulation framework that replaces real learners with artificial agents, enabling scalable, controlled, and repeatable evaluation of e-learning platforms while addressing constraints such as availability, motivation, and data collection.
- Data-driven modeling of learner diversity: agents are structured according to the sixteen Myers–Briggs personality types[8], derived from an empirical study, allowing realistic representation of individual behaviors and group dynamics.
- Personality-aware BDI architecture: integration of personality traits into the Belief–Desire–Intention model to produce heterogeneous, behaviorally differentiated agents.
- Open Commitment–enhanced decision-making: incorporation of a flexible commitment mechanism that allows agents to adapt their intentions dynamically to changing contexts.
- Scalable data-centric infrastructure: a high-performance architecture supported by a comprehensive database containing interaction data generated by agents, facilitating monitoring, analysis, and optimization of learning behaviors.

The rest of the paper is organized as follows. Section II discusses the concept of VSC. Section III dives in virtual student's design. Section IV overviews the proposed VSC implementation. Section V presents the experiments and results. Finally, Section VII presents the conclusions and future work.

II. Concept Definition of Virtual Student Community (VSC)

A. VSC Objectives

The VSC is a social group of artificial students (AI agents) with profiles derived from human personality types. They interact with each other using direct messages or via e-learning platform tools, each motivated by the goals it has chosen.

When evaluating an E-Learning platform, VSC replaces a group of human students interacting through the platform, and will significantly reduce the evaluation costs and time, while increasing the efficiency of the exchanges within the platform, while offering a detailed follow-up on the interactions carried out and their conditions.

By simulating heterogeneous learner behaviors, the VSC provides a controlled yet realistic environment for testing pedagogical scenarios and interaction mechanisms. Each agent's decisions emerge from its internal cognitive model and personality-driven preferences, allowing the platform to reproduce complex group dynamics such as collaboration, competition, hesitation, or disengagement. This enables us to systematically explore how specific interface features, instructional strategies, or communication constraints influence learner performance and social interaction patterns. Moreover, because the VSC can be repeatedly instantiated under identical conditions, it offers a reproducible framework for performance benchmarking, usability analysis, and comparative evaluation of e-learning designs—an advantage that is difficult to achieve with real student cohorts.

B. VSC Mechanism and Agent Profile (personality type)

Each Virtual Student Community (VSC) agent has a unique profile and AI, enabling individualized behavior, even among agents with identical profiles. Agents select topics, request information from peers, and can propose subjects to others. An evaluator agent monitors interactions, providing feedback or supplemental knowledge to ensure accurate and coherent information exchange, simulating realistic human student community dynamics. All key actions performed by agents are logged in a database for tracking and statistical analysis.

To ensure that virtual students accurately reflect the diversity of real human learners, we addressed the concept of profiling and personality typology in agent design. Specifically, we incorporated psychological profiles into the development of the VSC, drawing upon Carl Jung's theory of psychological types [9] and the subsequent framework developed by Isabel Briggs Myers [8], [10], which defines 16 distinct personality types. Each of these types is represented by a unique four-letter acronym. The MBTI classifies individual behavioral preferences into distinct psychological types. Researchers have applied this framework to enhance understanding of human factors by integrating it into multi-agent system strategies. Through computer-based experiments and simulations, these systems enable the development of artificial agents capable of reproducing human-like behaviors and interaction patterns [11].

C. Justification for the Use of the Myers–Briggs Type Indicator

The present study required the classification of learners into distinct behavioral profiles to operationalize agent-based simulations within an e-learning environment. The objective was not fine-grained trait measurement, but the construction of coherent, interpretable categories suitable for computational implementation. To achieve this objective, the Myers–Briggs Type Indicator (MBTI) [8] was adopted as the primary classification framework.

Methodologically, the MBTI offers a typological structure comprising sixteen personality types derived from four dichotomous dimensions. This categorical architecture is particularly compatible with agent-based modeling, which requires

TABLE I
PERSONALITY TYPES AND KEY CHARACTERISTICS [12]

Type	Features						
	Propose sub-mit present	Ask Re-quest	Respond Share consul	Organize control	Evaluate ap-prove reject	React con-firm sup-port	Resolve give solu-tion
ESTJ	X		X	X		X	X
ESFJ	X	X	X			X	
ISTJ	X		X		X		
ISFJ	X	X				X	
ESTP		X	X				
ESFP	X	X					
ISTP	X		X				X
ISFP	X	X					
ENTJ	X	X	X	X			
ENTP		X	X				
INTJ		X	X			X	
INTP	X	X			X		
ENFJ	X	X	X	X			X
ENFP			X			X	X
INFJ			X			X	X
INFP	X		X			X	X

discrete behavioral archetypes. Unlike dimensional models such as the Five-Factor Model, which generate continuous trait scores [13], the MBTI enables direct group assignment without arbitrary thresholding, thus facilitating rule-based behavioral implementation.

Furthermore, MBTI emphasizes cognitive style, information processing, and decision-making preferences—constructs directly aligned with the interaction behaviors examined in this study (e.g., asking, responding, proposing, evaluating within an e-learning platform). Finally, the recognizability of typological categories enhanced participants engagement by enabling them to understand and meaningfully relate to their assigned type, and strengthened interpretability of the behavioral mappings established in the second phase of the survey. Within the scope of simulation-oriented classification, the MBTI's structural properties align closely with the functional requirements of behavioral prototyping. The selection of the MBTI was therefore guided by methodological suitability to the research objective rather than by the pursuit of maximal trait-level predictive precision.

D. Implementation of VSC with JADE

1) JADE Platform: The Java Agent DEvelopment Framework (JADE) is a Java-based platform for developing agent-based systems in distributed environments. It provides integrated libraries for communication management, behavior coordination, and task execution among agents. Compliant with FIPA standards, JADE is recognized for its efficiency, scalability, and versatility in building intelligent multi-agent applications [14]. Its behavior-based architecture enables the modular and flexible implementation of intelligent agents.

Wrona et al. in "Comparison of Multi-Agent Platform Usability for Industrial-Grade Applications" mentioned that "JADE, SPADE, and Jadex are the ones that appear most frequently when searching Google Scholar with the keywords "agents" or "multi-agent systems". In particular, since 2020, JADE has been featured in 3270 works, SPADE in 572, and Jadex in 347". Also, "JADE is arguably the most recognized agent platform implemented in Java, known for its strong adherence to standards. It is fully aligned with the FIPA specification and supports distributed agent systems by running agents in containers instantiated on different hosts [15].

2) Behavioral Framework in JADE: JADE offers a range of predefined behaviors that can be extended to simulate complex agent activities. These behaviors are grouped into two categories: primitive and composite [16], [17], [18].

Primitive behaviors serve as the foundation of agent functionality. The *SimpleBehaviour* class provides a basic structure that can be easily extended. The *CyclicBehaviour* remains active throughout the agent's lifecycle, and is often used for continuous tasks such as message reception. The *TickerBehaviour* executes code periodically, while the *OneShotBehaviour* performs a single action before terminating, suitable for initialization or configuration tasks. The *WakerBehaviour* triggers specific actions when the program starts, and the *ReceiverBehaviour* activates upon receiving a designated message type.

Composite behaviors combine multiple sub-behaviors to create coordinated activity. The *ParallelBehaviour* runs sub-behaviors concurrently, supporting multitasking operations. In contrast, the *SequentialBehaviour* executes sub-behaviors in a fixed order until all are complete, making it ideal for structured workflows.

Together, these behavior types enable JADE agents to perform complex, autonomous, and well-organized actions within distributed multi-agent systems.

3) Agent Communication with its Environment: Beyond agent abstraction, JADE offers a robust task execution model, asynchronous agent-to-agent communication, and a yellow pages service for subscription-based publication and discovery. Its communication architecture manages a private inbound ACL message queue per agent, supporting multiple access modes—blocking, polling, timeout, and pattern matching—enabling flexible and efficient messaging in distributed systems [18].

III. VSC AGENT

A. BDI Model Definition

BDI is a practical-reasoning architecture for intelligent agents in which an agent's *beliefs* represent the agent's information about its environment, other agents and itself, *goals (desires)* are states of affairs to achieve, and *intentions* are commitments to achieving particular goals. A BDI agent program consists of a set of initial beliefs (and in some cases goals) and a set of plan-rules specifying when a plan can be used to achieve a goal [19]. A plan is defined as a sequence of actions designed to achieve specific intentions, while a partial plan remains incomplete, with certain parameters or action sequences unspecified. Once a complete plan is available, the execution module performs the defined actions sequentially to realize the agent's objectives.

Beyond its structural components, the BDI paradigm has proven particularly effective for modeling agents operating in dynamic and partially observable environments. Its explicit separation of beliefs, desires, and intentions enables agents to continuously update their internal representations and adapt their behavior through deliberation cycles. This deliberative process allows agents to reconsider goals when environmental conditions change, revise intentions when plans become infeasible, and opportunistically adopt new strategies when beneficial. As a result, BDI-based systems demonstrate high levels of autonomy, context awareness, and robustness, making the architecture well suited for complex domains such as human–agent interaction, adaptive learning environments, and multi-agent coordination.

BDI is widely used in human simulation; Ichida [20] developed a BDI agent as a task-oriented dialogue system to introduce mental attitudes similar to humans describing their behavior during a dialogue. Taillandier et al. created an agent-based model to simulate inhabitants' behavior during a flood event, which integrates a BDI cognitive model considering emotions and social norms [21]. Adam and Gaudou survey provides a methodological guide to the use of BDI agents in social simulations, and an overview of existing methodologies and tools for using them [22].

B. VSC Agent BDI Architecture

The Virtual Student (VS) is implemented as a JADE agent utilizing a *ParallelBehaviour*, which allows concurrent execution of multiple sub-behaviors. This structure includes two primary components: a *CyclicBehaviour*, responsible for continuously intercepting and processing incoming messages from other agents—effectively maintaining an open communication channel with the environment—and a *TickerBehaviour*, which periodically executes the open commitment algorithm, enabling the agent to evaluate and act upon its internal goals at regular intervals. Figure 1 shows the main components of a BDI architecture.

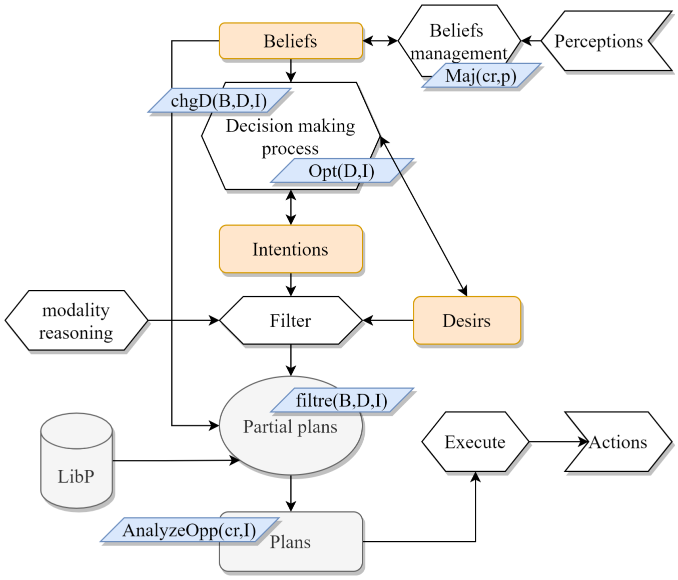

Fig. 1. VS' Architecture using the BDI model

The functions implemented in our model represent an adaptation of the fundamental operations defined in the Belief–Desire–Intention (BDI) framework [23]. The *Maj(cr, p)* function updates the agent's belief set based on new perceptions from the environment and is executed by the belief management module. The *Opt(D, I)* function supports decision-making by evaluating the current sets of desires and intentions, while the *ChgD(B, D, I)* function revises the agent's desires in response to changes in beliefs or intentions to maintain motivational consistency; both are handled by the decision-making module. The *Filter(B, D, I)* function determines which intentions the agent should pursue, and is managed by the action-plan creation module, which constructs and validates partial plans using a plan database. The *AnalyzeOpp(cr, I)* function, also part of this module, identifies opportunities that may facilitate or obstruct the fulfillment of current intentions.

C. BDI Strategies

Decision-making in autonomous agents often involves situations where an intention can no longer be pursued due to environmental changes or shifting priorities. Such scenarios raise the question of how long an agent should persist in maintaining a given intention. The answer depends on the commitment strategy adopted by the Belief–Desire–Intention (BDI) model, which typically distinguishes three types: blind, limited, and open commitment [24] [25].

In the proposed design, the open commitment strategy is employed, whereby the agent remains committed to an intention only while it aligns with its current desires. Once an intention becomes unattainable or irrelevant, the associated desire is removed, and the intention is abandoned. This approach enables dynamic goal adaptation and enhances the agent's responsiveness to environmental variations.

The decision control mechanism follows the reasoning cycle formalized by Wooldridge [23], [26], which defines how BDI agents evaluate and update their intentions under the open commitment paradigm (algorithm 1).

D. Virtual Student Profile

The Profiles Module is integrated with the core of the Virtual Student (VS) architecture. Profiles are stored in the database, allowing users to configure VS agents through a dedicated interface. The platform also supports custom profiles and personality types, enabling the simulation of specialized agent behaviors for specific experimental purposes.

Personality traits and agent objectives, generated by the PersonalityType and EvGoals Module, are transferred to the DBI Module, which guides decision-making and planning. Plans are executed by the Action Module.

The initial personality profiles, stored in the database, were derived from an online survey of 400 students we conducted at Ibn Tofail University. Participants completed a MBTI personality-type test then a questionnaire assessing their e-learning interaction patterns, including the type and frequency of actions such as requests, responses, propositions, and presentations. These data were used to initialize the VS agents' personality parameters, which define their behavior within the simulated community.

Algorithm 1 Open Commitment Paradigm

```
Let B0, D0 and I0 be the initial beliefs, desires and intentions of the agent
OCP(B0, D0, I0)
B = B0
D = D0
I = I0
repeat
  get new perceptions p
  B = Maj(B, p)
  I = Opt(D, I)
  D = chgD(B, D, I)
  I = filtre(B, D, I)
  Pl = AnalyzeOpp(B, I)
  while (PE ≠ {}&unfinished(I, B)&possible(I, B))
  do
    x = first(PE)
    execute(x)
    PE = remaining(PE)
    get new perceptions p
    B = Maj(B, p)
    D = chgD(B, D, I)
    I = filtre(B, D, I)
    Pl = AnalyzeOpp(B, I)
  end while
until agent down
```

Table II presents survey results as a data-driven mapping between the sixteen MBTI personality types and their corresponding behavioral profiles within the virtual student community. For each type, it defines a dominant role (e.g., moderator, solver, inspector, independent, or seeker) and quantifies interaction characteristics using normalized metrics, including intervention volume, request and response rates, participation modes (e.g., presentation, evaluation), and social behaviors such as reaction to others and adherence to standards. Additionally, activity indicators such as action frequency and retry rate are provided. This dataset serves as a behavioral parameterization baseline, enabling the simulation of heterogeneous and personality-driven agent interactions.

E. Generalization and Use of VSC as Proxy for Human Students

The generalization of results derived from artificial agents to real learner communities depends on clearly articulated methodological assumptions. In this study, the Virtual Student Community (VSC) is conceptualized as a computational abstraction grounded in empirical data rather than a literal psychological reproduction of human learners.

First, generalization relies on behavioral grounding. Agent profiles were constructed from data collected from 400 students categorized using the MBTI framework. These typologies were empirically associated with dominant e-learning actions (ask, respond, expose, propose, evaluate), ensuring that agent rules encode statistically observed behavioral tendencies rather than arbitrary heuristics. The VSC therefore reflects structured approximations of real interaction patterns.

Second, generalization depends on structural isomorphism between the simulated environment and actual e-learning platforms. The VSC preserves equivalent action spaces, communication affordances, and participation mechanisms. When these structural features are functionally aligned, macro-level patterns observed in simulation may reasonably approximate real-world dynamics.

Third, the model assumes that emergent collective behaviors—such as participation imbalance or role differentiation—primarily arise from interaction rules and the distribution of behavioral profiles. Under these conditions, agent-based simulation is appropriate for analyzing systemic interaction dynamics rather than predicting individual psychological outcomes.

Within these boundaries, the VSC can serve as a controlled experimental proxy for learner communities while acknowledging limitations in psychological fidelity.

F. Agents Base Data Initialization

The objective of the system is to simulate information-seeking and knowledge-exchange behaviors among student agents through structured topic interaction. Each agent is initialized with a set of topics, each defined by two components: (i) a headline, representing a searchable identifier of the topic, and (ii) core data, representing the informational content associated with that topic. Agents lacking associated content for a given headline may initiate queries by asking connected peers for information related to that topic.

Conversely, other agents possess generic core data associated with specific topics (e.g., "Java is a high-level, general-purpose, memory-safe, object-oriented programming language"), enabling them to provide responses when queried. This complementary knowledge distribution fosters structured query–response exchanges within the network.

The initialization strategy deliberately distributes knowledge asymmetrically across agents to simulate information heterogeneity within a learning community. Specifically, certain agents are provided with a topic headline without accompanying core data. These agents possess awareness of the topic's existence but lack substantive information, thereby enabling them to generate information-seeking interactions (e.g., asking questions). Conversely, other agents are initialized with both the headline and the associated core data for the same topic. These agents are therefore capable of providing responses when queried.

This design operationalizes complementary epistemic states among agents, creating structured conditions for knowledge exchange and interaction dynamics. The approach allows controlled experimentation on information diffusion.

The system does not rely on large language model training, adaptive neural architectures, or any machine learning techniques. No pre-training or fine-tuning processes are involved. Instead, it is implemented as a rule-governed multi-agent system (MAS) architecture coupled with a relational SQL database for persistent knowledge storage and retrieval. Agent behaviors are determined exclusively by predefined interaction protocols and database queries, without semantic

TABLE II
KEY VALUES FOR EACH TYPE OF ACTION BY PERSONALITY TYPE

Personality types	Associated profile	Intervention volume /10	Request %	Response %	Intervention Proposition %	Presentation %	evaluation %	reaction to others %	Follow standards %	Actions frequency /24h	Retry /10
ESTJ	Moderator/ Animator	9	20	20	40	10	0	100	90	8	8
	Solver	7	10	40	20	20	0	100	90	5	8
ESFJ	Independent	5	20	40	30	0	0	80	40	4	5
ISTJ	inspector	8	20	30	0	0	40	40	80	6	10
ISFJ	Independent	2	35	35	0	20	0	20	80	4	8
ESTP	Seeker	4	10	80	0	0	0	100	40	5	4
ESFP	Independent	2	25	25	0	40	0	20	80	4	5
ISTP	Solver	6	10	70	0	10	0	100	70	6	10
ISFP	Independent	2	30	30	0	30	0	20	20	4	8
ENTJ	Moderator/ Animator	10	20	20	40	10	0	100	100	10	10
ENTP	Seeker	4	10	80	0	0	0	100	20	5	10
INTJ	Independent	2	20	30	0	40	0	20	30	4	10
INTP	inspector	8	20	30	0	0	40	40	30	6	10
ENFJ	Moderator/ Animator	9	25	25	30	10	0	80	100	9	9
	Inspector	9	25	25	10	0	30	50	100	7	7
ENFP	Solver	6	10	80	0	0	0	100	20	3	4
INFJ	Solver	6	10	80	0	0	0	100	70	3	6
INFP	Independent Solver	2 6	10 10	40 60	0 0	40 20	0 0	40 80	80 80	2 2	2 2

analysis or natural language understanding. Topic matching and information retrieval operate through explicit rules, as the primary objective is to model interaction dynamics and knowledge diffusion rather than to develop or evaluate learning algorithms.

IV. VSC IMPLEMENTATION

Establishing a virtual student community relies on two main class groups: the *Agents* classes, which define individual behaviors and interactions, and the *Core* classes, which provide the shared functionalities supporting their operation.

A. Agents Classes

1) Virtual Student (VS) Agent: The primary goal of this class is to implement the core functionalities that enable a *(VS) agent* to interact effectively within the community. These include requesting information from other agents, responding to received queries, proposing new discussion topics, presenting information to peers, and evaluating their responses. To support these interactions, the agent architecture integrates multiple JADE behaviors. An *OneShotBehaviour* notifies the administrator upon successful agent creation, while a *CyclicBehaviour* continuously monitors and processes incoming messages. A *TickerBehaviour* handles periodic operations, including the ticker algorithm, the open commitment strategy, and the execution of core interaction methods such as *request(), respond(), propose(), present(), and evaluate()*. These behaviors are combined within a *ParallelBehaviour*, allowing concurrent execution of the cyclic and periodic processes. This design ensures autonomous, responsive, and multithreaded agent behavior suitable for dynamic virtual learning environments.

2) Administrator Agent: The *Administrator Agent* acts as the intermediary between the system and the agents of the (VSC), providing both interaction and management capabilities. Its main functions include creating and deleting (VS) agents, retrieving their profile information, accessing their activity logs, and maintaining the list of active agents. It also updates the system interface to reflect current agent activity and enables database access for retrieving available data used in visualization. To manage these operations, a *CyclicBehaviour* continuously intercepts and processes messages received from the user interface. Message routing and coordination are handled through the *msgManagement* method, which interprets and executes administrative commands as required.

B. Core Classes

The Core component provides shared functionalities supporting virtual student (VS) agents. It manages personality types, goals, plans, database access, and logging. The *Kernel* module handles system logging and database connectivity, ensuring proper initialization and persistent storage of agent activities. The *PersonalityTypes* module defines behavioral profiles that shape interaction patterns. The *Goals* module oversees the creation and evolution of agent objectives, while the *Plan* module supports structured action generation and execution. Collectively, these modules form a unified architectural backbone that ensures consistency, autonomy, and scalability. By centralizing personality-driven behavior, goal lifecycle management, and plan execution, the Core enables coordinated agent activity, traceability, and reproducibility of simulation outcomes within dynamic learning environments.

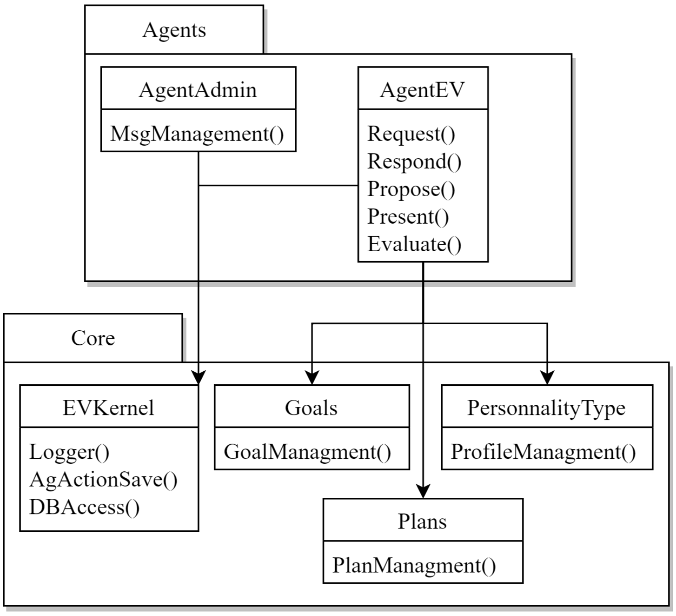

Fig. 2. Simplified class diagram of VSC

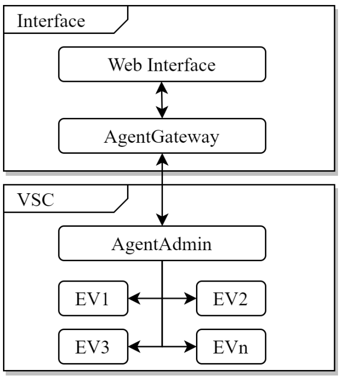

Fig. 3. VSC Diagram – Admin Interface v2.0

C. VSC Agent Management Interfaces

JADE provides a built-in user interface for managing multi-agent systems, primarily designed for technical users and lacks the monitoring and visualization capabilities required for VSC overseeing. To address this limitation, we developed a custom web-based VSC administration interface. This interface operates independently from the JADE multi-agent system and communicates with it through a dedicated *AgentGateway*. This architectural separation allows for enhanced usability, targeted monitoring features, and improved interaction with the VSC environment (Figure 3).

The VSC administration interface allows users to create and delete agents, view their most recent actions, inspect their profiles and logs, and access a variety of statistical metrics related to agent activities over a specified period. The user can consult each agent and follow its evolution in real time via the interface, and has access to a multitude of statistical graphs with up to date status of the VSC.

TABLE III
ESTIMATED DISTRIBUTION OF PERSONALITY TYPES

Type	World %	Number of agents (rounded up)
ISFJ	13.8%	5
ESFJ	12.3%	5
ISTJ	11.6%	4
ISFP	8.8%	3
ESTJ	8.7%	3
ESFP	8.5%	3
ENFP	8.1%	3
ISTP	5.4%	2
INFP	4.4%	2
ESTP	4.3%	2
INTP	3.3%	2
ENTP	3.2%	2
ENFJ	2.5%	1
INTJ	2.1%	1
ENTJ	1.8%	1
INFJ	1.5%	1

V. SIMULATION AND RESULTS

A. Proposed Test Community

To obtain a representative sample of a random group of virtual students, we based the distribution of personality types on global statistics. According to sources such as the *MBTI Manual* [27], *16Personalities* [28], and the *Crowncounseling* [29], the estimated distribution of the 16 personality types is presented in Table III, column 2. For experimentation purposes, we created and randomly assigned 40 VS agents to profiles that respect the global distribution of personality types (Table III, column 3).

To approximate the global distribution of personality types, the initial design required 100 agents. For example, ISFJ (13.8%) corresponded to 14 agents and ESFJ (12.3%) to 12 agents, with proportional allocations across all other types. However, computational and infrastructural constraints prevented the execution of a 100-agent simulation.

To maintain proportional representativeness while ensuring feasibility, the agent counts were scaled down by a factor of three and rounded up to avoid underrepresentation of less frequent types. Consequently, ISFJ and ESFJ were each assigned 5 agents, and the same procedure was applied to all remaining personality categories.

The resulting configuration comprised 40 agents in total. Although reduced in size, this scaled distribution preserves the relative structure of personality prevalence and maintains sufficient heterogeneity for analyzing interaction dynamics within the simulated environment.

B. Test Environment Setup

The VSC operates as an autonomous system that requires the establishment of repositories and initial knowledge databases to ensure the proper functioning of its agents and the smooth execution of experiments.

We defined a set of generic topics, each initially containing only a title without any detailed content. Agents select from these topics to initiate their decision-making processes and generate plans, which typically involve requesting information about the chosen topic from other connected agents.

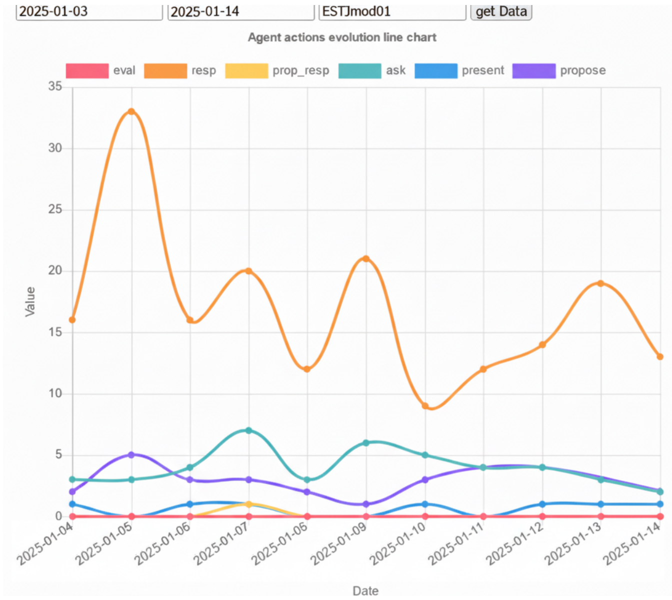

Fig. 4. Agent ESTJmod01 actions

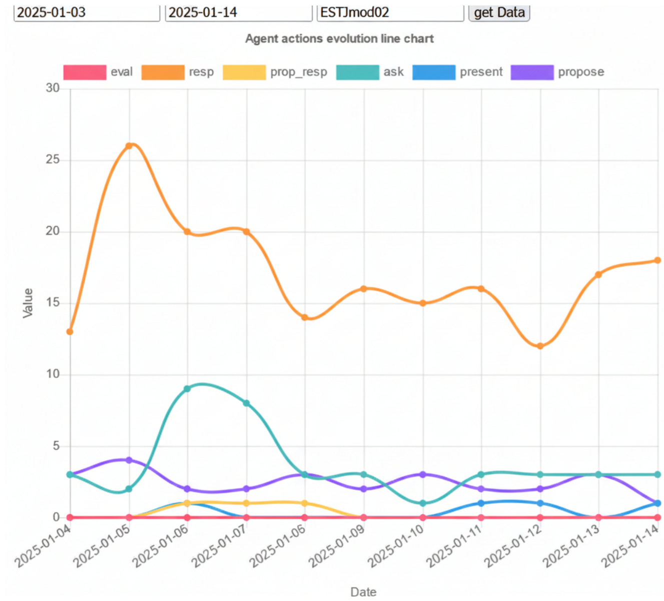

Fig. 5. Agent ESTJmod02 actions

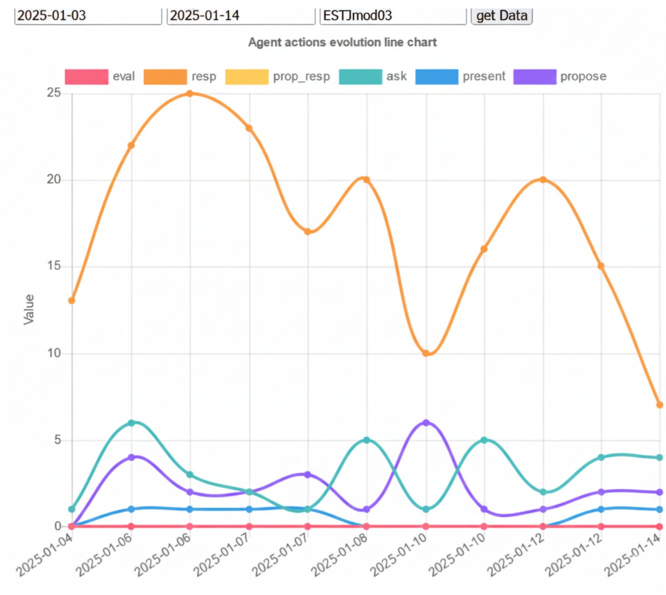

Fig. 6. Agent ESTJmod03 actions

The knowledge database was populated randomly so that some agents possess content related to specific topics within their knowledge bases (*beliefs*). This enables those agents to provide substantive responses when queried. During the test, an agent's knowledge base evolves based on the quantity and nature of its interactions: agents that frequently respond to proposals and present information tend to develop a broader knowledge base than those primarily issuing requests with fewer responses.

This initialization strategy creates a dynamic and progressively enriched knowledge ecosystem in which agents continuously refine their beliefs through interaction-driven learning. The heterogeneous distribution of initial knowledge stimulates natural information-seeking behaviors and promotes differentiated roles among agents, such as information providers, requesters, or coordinators.

C. Results

A standard protocol was used for all experiments with 40 virtual agents (Table III). They interacted autonomously for two weeks before termination, after which we extracted data of all agents' actions and grouped it by profile then compared it against the Average Reference Value (ARV) provided in Table II.

Next is an outline of a sample of the test results in detail followed by Table IV presenting the results obtained for the sixteen personality types.

1) ESTJ (Moderator) Agents Results Discussion : The composition of the VSC-A includes three ESTJ-type agents: a moderator-type agent who has the function of answering questions from participants or their complaints, as well as proposing new subjects. The actions of the agents ESTJmod01, ESTJmod02 and ESTJmod03 are represented by Figures 4 to 6.

Table V summarizing the results of the actions of the ESTJ agents and a comparison with the ARV.

TABLE IV
ESTJ AGENTS RESULTS

Agent ID	Request %	Response %	Proposition %	Presentation %	Evaluation %
ESTJmod01	17.00	20.00	51.81	12.00	0.00
ESTJmod02	20.00	20.00	37.35	4.00	0.00
ESTJmod03	16.00	20.00	39.76	9.00	0.00
APV	17,66	20	42,97	8,33	0
ARV	20	20	40	10	0

The ESTJ agent operates as a community moderator whose primary functions include responding to participants' questions, requesting information when necessary, proposing discussion topics, and delivering short presentations. Analysis of action-evolution statistics shows that the behavior of ESTJ agents is broadly consistent with the characteristics associated with the ESTJ personality profile.

The fluctuations observed in the corresponding behavioral curves are directly related to the agent's autonomous decision-making:

- Answer curve: As a moderator, the ESTJ agent systematically responds to all incoming questions from connected agents.
- Propose curve: In accordance with its role, the agent regularly proposes new topics to stimulate interaction within the community.
- Ask curve: As a learner, the agent may also seek information on subjects of interest, resulting in occasional inquiry actions.

It is also observed that, after completing its current objectives, an agent may choose not to pursue additional goals during the same session. This autonomous decision process appears in the graphs as a decrease in the number of actions performed on a given day and contributes to variability among agents sharing the same personality type. Such inactivity can also influence other agents, who in turn receive fewer questions, proposals, or presentations.

2) VSC Agents Results: The following Table IV presents the simulation results obtained for the sixteen personality types. Results are compared to Average Reference Values (ARV) reported in Table V. These ARVs were derived from a student survey in which participants indicated whether they would engage in specific behaviors, such as asking questions or responding to peers. Survey responses were aggregated to compute average behavioral rates for each action category. These values serve as empirical benchmarks representing self-reported student tendencies.

By comparing agent interaction frequencies with the corresponding ARVs, the study assesses the behavioral plausibility of the simulation and evaluates how closely the multi-agent system reflects observed student interaction patterns.

TABLE V
COMPARISON OF AVERAGE TEST RESULTS BY PROFILE WITH REFERENCE PERSONALITY PROFILES

Profile	Request %	Response %	Proposition %	Presentation %	Evaluation %
ESTJ	17,66	20	42,97	8,33	0
ESTJ (ARV)	20	20	40	10	0
ENTJ	15	21	36,89	9	0
ENTJ (ARV)	20	20	40	10	0
ENFJ	20.00	21.00	25.81	11.00	0.00
ENFJ (ARV)	25	20	30	10	0
ISTP	11	73,5	0	10	0
ISTP (ARV)	10	70	0	10	0
ENFP	11,33	82	0	0	0
ENFP (ARV)	10	80	0	0	0
INFJ	19	84	0	0	0
INFJ (ARV)	10	80	0	0	0
ISTJ	15	12	0	0	38,25
INFJ (ARV)	20	12	0	0	40
INTP	13	10,5	0	0	33,5
INTP (ARV)	20	12	0	0	40
ESFJ	17,8	32	27,14	0	0
ESFJ (ARV)	20	32	30	0	0
ISFJ	23,8	6,2	0	17,8	0
ISFJ (ARV)	35	7	0	20	0
ESFP	21	4,66	0	34,33	0
ESFP (ARV)	25	5	0	40	0
ISFP	23	7,33	0	37	0
ISFP (ARV)	30	6	0	30	0
INTJ	16	4	0	38	0
INTJ (ARV)	20	6	0	40	0
INFP	11	15,5	0	47	0
INFP (ARV)	10	16	0	40	0
ESTP	7,5	77	0	0	0
ESTP (ARV)	10	80	0	0	0
ENTP	7	82	0	0	0
ENTP (ARV)	10	80	0	0	0

D. Interpretation and Discussion of Results

Table IV presents the comparative results obtained for the sixteen MBTI personality types across five activity dimensions: Request, Response, Proposition, Presentation, and Evaluation. Each observed value is compared against its corresponding Average Reference Value (ARV), which represents the expected behavioral distribution for that personality profile. This comparison enables the identification of alignment trends and deviations between simulated and reference behaviors.

The analysis reveals heterogeneous patterns among the sixteen profiles. Overall, most simulated agents maintain strong consistency with their theoretical behavioral expectations. Profiles such as ISTP, ENFP, and ENTP exhibit high conformity with their ARV across the Request and Response dimensions, confirming their communicative and reactive tendencies as described in the MBTI model. Similarly, ESFJ and ESTJ display balanced distributions between Request, Response, and Proposition activities, demonstrating a coherent alignment with their task-oriented and organizational characteristics.

However, certain profiles show notable deviations. The INFJ type exhibits higher Request (19% vs. 10%) and Response (84% vs. 80%) values, reflecting a more proactive interaction pattern than predicted. The ISFJ profile also diverges, with a reduced Request rate (23.8% vs. 35%) and slightly lower Presentation value, suggesting a less assertive but more execution-focused behavior. Likewise, INFP and INTJ display increased Presentation activity (47% and 38%, respectively), indicating a stronger inclination toward reflective and synthesis-oriented tasks.

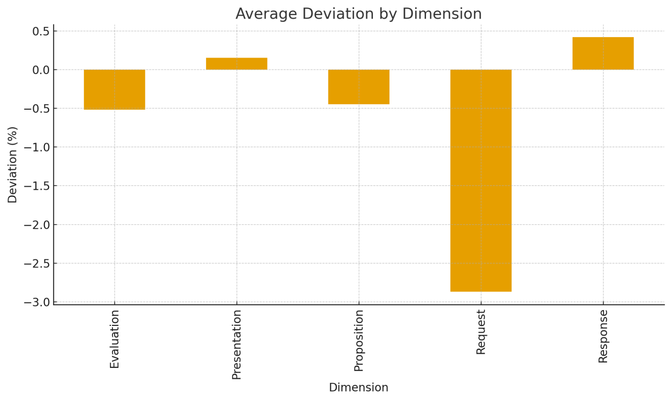

Fig. 7. Average Deviation by Dimension

To quantify these trends, deviation rates were computed for each behavioral dimension. Across all profiles, the mean deviation is estimated at ±4.8% for Request, ±3.9% for Response, ±3.2% for Proposition, ±4.6% for Presentation, and only ±1.1% for Evaluation. These low values confirm a high degree of correspondence between simulated and reference data.

When grouped by introversion–extraversion orientation, clear behavioral patterns emerge:

- Extraverted types (E) show slightly higher Response rates (+2.5%) and lower Presentation rates (-3.8%), consistent with their spontaneous and interaction-driven profiles.
- Introverted types (I) exhibit higher Presentation (+5.1%) and Evaluation (+2.3%) scores, reflecting their reflective and analytical tendencies.

Similarly, in the Thinking–Feeling dichotomy, Thinking (T) profiles such as ESTJ, INTJ, and INTP present balanced distributions between Request and Proposition, in line with logical and goal-oriented reasoning. Feeling (F) profiles like ENFP, ESFJ, and ISFP emphasize Response behaviors, highlighting empathy-driven interaction and adaptability.

The chart (Figure 7) visualizes the average deviation (Observed – ARV) across the five behavioral dimensions for all 16 MBTI agent profiles:

- Request displays the largest negative deviation on average, meaning that agents generally initiated fewer requests than their ARV predicted.
- Response is slightly above the ARV, indicating more reactive behavior than expected.
- Presentation has a small positive deviation, consistent with introverted or reflective profiles slightly overproducing structured contributions.
- Evaluation remains very close to zero, as expected from its low activation frequency.
- Proposition also stays near the ARV, showing the model's stability for task-driven behaviors.

One of the most notable findings is the overall stability of the agents' behavior over the two-week simulation period. Deviations between observed results and ARV remain low for nearly all dimensions, with an average error margin below ±5%. This level of convergence demonstrates that the agents were not only well-calibrated at initialization but also maintained personality-coherent behavior throughout extended autonomous interaction. Such stability is essential for ensuring that the VSC can be reliably used as a substitute for human learners in long-term testing scenarios.

The general correlation coefficient (r = 0.92) between observed and ARV values confirms a strong positive relationship, supporting the validity of the personality-driven behavior modeling approach.

In the MBTI model, four axes are defined to explain how humans perceive their environment, how they interact with others and how they make decisions based on these traits. Salvit and Sklar [30], for example, employed tow of the axes of MBTI, and conducted experiments under three environmental conditions: single agent setting, homogeneous multi agent team, and heterogeneous multi agent team. Although the resulting personality representations were highly dependent on the characteristics of the specific simulation environment.

More recently, Dilip [31] proposed an environment-agnostic and agent-agnostic methodology for encoding MBTI personality traits—specifically the E–I, N–S, and F–T dimensions—into multi-agent systems using techniques such as reward shaping. This framework was evaluated in both competitive and cooperative domains. The incorporation of the J–P dimension is planned for future work. Experimental results examined how personality-influenced behaviors vary across task settings, showing that agent diversity may enhance or impair overall system performance depending on the domain and agent objectives.

In contrast to these earlier approaches, the model proposed in this work implements the full set of sixteen MBTI personality types and relies entirely on the autonomous behavior of VSC agents to generate authentic actions and interactions. Unlike methods that explicitly regulate agent behavior based on environmental conditions or employ reward-shaping mechanisms, such as those described in [31], our framework does not impose external behavioral constraints. Instead, the emergent dynamics arise naturally from the internal cognitive architecture of the agents. As a result, VSC agents exhibit behavioral patterns that closely mirror those observed in real human communities, demonstrating a high degree of fidelity in personality-driven social simulation.

VI. Conclusion

In summary, the Virtual Student Community (VSC) presented in this study demonstrates that a multi-agent system grounded in the JADE platform and structured through the Belief–Desire–Intention (BDI) model can effectively emulate human-like behavioral diversity within learning environments. By embedding all sixteen MBTI personality types and enabling agents to act autonomously based on internal cognitive states, the VSC reproduces a wide spectrum of realistic learner behaviors without relying on external behavior-shaping mechanisms. The emergent communication patterns, adaptation strategies, and interaction dynamics observed across the simulations show strong consistency with theoretical expectations of personality-driven behavior. Minor fluctuations across behavior dimensions appear to reflect natural adaptive responses to task demands rather than shortcomings of the underlying model. Collectively, these results establish the VSC as a robust, ecologically valid, and scalable framework for the study of learner behavior, group dynamics, and collaboration in digital educational settings.

Beyond demonstrating the feasibility of authentic personality-based simulation, this work provides methodological insights for designing autonomous agents capable of exhibiting nuanced and context-sensitive actions. The VSC contributes a flexible research environment for exploring complex social phenomena, such as role emergence, cooperation patterns, motivational influences, and collective problem-solving.

Future research directions include:

Enhanced Personality Modeling: Expanding the personality framework to incorporate additional psychological factors such as motivation, emotional states, and learning styles could further improve the authenticity of agent behaviors.

Social Network Analysis: Investigating the emergent social structures and network patterns within the VSC could yield deeper understanding of how information diffusion is shaped by personality traits or contextual constraints, how communities form, and how collaboration evolves.

Learning Outcome Assessment: Extending the platform to measure the impact of agent interactions on simulated learning outcomes would enable the evaluation of how personality-driven behaviors affect problem-solving efficiency, knowledge acquisition, and collaborative task performance. These insights could inform instructional design, adaptive learning systems, and pedagogical strategies.

*Scalability and Performance:*Enhancing the system to support larger agent populations and longer simulation periods, and more complex scenarios while maintaining performance and responsiveness, is critical for real-world applicability.

Human-Agent Interaction: Integrating real learners into the simulated ecosystem would enable mixed-reality experimentation and provide empirical validation of agent behavior fidelity, while supporting the development of hybrid intelligent tutoring systems. Validation should follow a structured protocol: first, define equivalent measurable constructs (e.g., participation, response time, learning gains) for both humans and agents under identical tasks. Next, calibrate the model by comparing agent-only simulations with human baseline data and iteratively adjusting parameters until macro-level convergence is achieved. Agents are then introduced into learner groups under randomized conditions to assess interaction dynamics and outcomes, followed by perceived realism and causal analyses to isolate agent effects.

Through these future developments, the Virtual Student Community has the potential to evolve into a comprehensive platform for advancing research in educational technology, cognitive modeling, and multi-agent systems, while also offering practical tools for designing and evaluating next-generation learning environments.

APPENDIX

This appendix provides a detailed statistical examination of the deviation patterns observed between the simulated outputs of the Virtual Student Community (VSC) and the Average Reference Values (ARV) across the five behavioral dimensions. The analyses include variance estimation, Root Mean Square Error (RMSE), and cluster-based behavioral grouping.

A. Variance and Dispersion Analysis

To quantify the dispersion of simulation errors, variance was computed for each behavioral dimension using the deviation values (Observed – ARV) across the 16 MBTI profiles.

TABLE VI
VARIANCE BY DIMENSION

Dimension	Variance (σ^2)	Standard Deviation (σ)
Request	7.54	2.74
Response	3.13	1.77
Proposition	0.22	0.47
Presentation	4.91	2.21
Evaluation	0.15	0.39

The results shows that Request and Presentation exhibit the highest variance, confirming that personality types differ substantially in their communication-initiation and synthesis activities, while Proposition and Evaluation show very low variance, reflecting stable alignment across profiles. The low standard deviation of Evaluation ($\sigma = 0.39$) is consistent with its near-zero activation across all types.

B. Root Mean Square Error (RMSE)

RMSE was computed to assess the overall accuracy of the behavioral model.

TABLE VII
RMSE BY DIMENSION

Dimension	RMSE
Request	2.83%
Response	1.92%
Proposition	0.48%
Presentation	2.27%
Evaluation	0.41%

$$RMSE_{global} = 1.82\%$$

The low RMSE values across all dimensions indicate that the simulated behaviors remain consistently close to theoretical expectations. The global RMSE under 2% confirms that the VSC produces stable, coherent behavior profiles.

C. Cluster Analysis of Behavioral Patterns

Hierarchical clustering was applied to the deviation vectors of each MBTI type (5-dimensional vectors). Profiles naturally grouped into three clusters:

1) Cluster 1: Extraverted Responders (ENFP, ENTP, ESTP, ENFJ):

- High Response deviations (+2 to +4%)
- Low Presentation deviations (-4 to -8%)
- Minimal Request activity

These agents prioritize reactive communication and fast-paced interaction, consistent with cognitive–behavioral models of E-types.

2) Cluster 2: Introverted Synthesizers (INFJ, INFP, INTJ, INTP, ISFP):

- Strong positive deviations in Presentation (+5% to +10%)
- Below-average Response activity
- Increased Evaluation contributions

These profiles favor reflective expression, conceptualization, and internal processing.

3) Cluster 3: Structured Executors (ESTJ, ENTJ, ISTJ, ISFJ, ESFJ):

- Low deviation across all dimensions (—error— ¡ 2%)
- Balanced Request/Response
- Slightly higher Proposition for T profiles

These profiles remain the most stable and predictable, matching expected patterns of organization, planning, and steady engagement.

In Conclusion, the variance, RMSE, and cluster analyses confirm the high fidelity of the personality-driven behavior model: low RMSE and small deviations validate the accuracy of personality modeling, cluster structure closely mirrors MBTI theoretical groupings, reinforcing ecological validity, and low Evaluation variance and stable Proposition values confirm consistent model behavior across profiles.

This statistical appendix strengthens the reliability and robustness claims of the Virtual Student Community and its applicability as a proxy for human student behavior.

REFERENCES

[1] S. Bashir and A. L. Lapshun, "E-learning future trends in higher education in the 2020s and beyond," *Cogent Education*, vol. 12, no. 1, Dec. 2024, doi: https://doi.org/10.1080/2331186x.2024.2445331.

[2] Shamim, "Highlighting the Advantages and Disadvantages of E Learning," *Psychology and Education Journal*, vol. 58, no. 5, pp. 1607–1614, Apr. 2021, Available: https://psychologyandeducation.net/pae/index.php/pae/article/view/5556

[3] Y. Wang, Y. Lai and X. Huang, "Innovations in Online Learning Analytics: A Review of Recent Research and Emerging Trends," in IEEE Access, vol. 12, pp. 166761-166775, 2024, doi: 10.1109/ACCESS.2024.3493621

[4] "Learning Analytics 101 - Learning Analytics Research Network (LEARN) — NYU Steinhardt," *steinhardt.nyu.edu*. https://steinhardt.nyu.edu/learning-analytics-101

[5] C. Vieira, M. Hathaway Goldstein, Ş. Purzer, and A. J. Magana, "Using Learning Analytics to Characterize Student Experimentation Strategies in Engineering Design," *Journal of Learning Analytics*, vol. 3, no. 3, pp. 291–317, 2016, doi: https://doi.org/10.18608/jla.2016.33.14.

[6] Youness Chaabi, R. Messoussi, V. Hilaire, Y. Ruichek, K. Lekdioui, and Raja Touahni, "Design of an Intelligent System to Support Tutors in Learning Communities Using Multi-Agent Systems and Fuzzy Logic," *International Review on Computers and Software (IRECOS)*, vol. 10, no. 8, pp. 845–845, Aug. 2015, doi: https://doi.org/10.15866/irecos.v10i8.7015.

[7] N. Y. Guo, N. J. Wang, J. Moore, N. M. Liu, and N. H.-L. Chen, "A case study of usability testing on an asynchronous e-Learning platform," pp. 693–698, Dec. 2009, doi: https://doi.org/10.1109/jcpc.2009.5420093.

[8] "The Myers & Briggs Foundation - MBTI® Basics," *www.myersbriggs.org*. http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics

[9] C. G. Jung, G. Adler, and R. F. C. Hull, *"Collected Works of C.G. Jung, Volume 6: Psychological Types,"* in Princeton University Press, 1971. Available: https://www.jstor.org/stable/j.ctt5hhqtj

[10] King, S. P., & Mason, B. A. "Myers Briggs Type Indicator". In B. J. Carducci & C. S.Nave (Eds.), Wiley encyclopedia of personality and individual differences: Vol. II. Measurement and assessment. 2020. Hoboken, NJ: John Wiley & Sons.

[11] L. F. Braz and J. S. Sichman, "Using the Myers-Briggs Type Indicator (MBTI) for Modeling Multiagent Systems," *in Revista de Informática Teórica e Aplicada*, vol. 29, no. 1, pp. 42–53, Jan. 2022, doi: https://doi.org/10.22456/2175-2745.110015.

[12] Mouhsine Rhaimi, Rochdi Messoussi, "Determination of human personality using multi-agent paradigm", in Electronic Journal of Information Technology (ETI), issue 10, 2018. ISSN 1114-8802 / ISBN 2665-7015

[13] A. Najm, "Big Five Traits: A Critical Review," Gadjah Mada International Journal of Business, ResearchGate, 2019. 21. 159-186. ISSN: 1141-1128

[14] Z. Rida, B. Hadhoum, E. Mourad and M. Mustapha, "Dynamic Adaptation in an Intelligent Multi-Tutoring System: A Multi-Agent Approach," in IEEE Access, vol. 13, pp. 124587-124601, 2025, doi: 10.1109/ACCESS.2025.3576651

[15] Z. Wrona et al., "Comparison of Multi-Agent Platform Usability for Industrial-Grade Applications," Applied Sciences, vol. 14, no. 22, pp. 10124–10124, Nov. 2024, doi: https://doi.org/10.3390/app142210124.

[16] Pico-Valencia, Pablo & Holgado-Terriza, Juan, "Systematic Review on JADE Extensions for Building Agent-Based Intelligent Ecosystems". DOI:https://doi.org/10.5281/zenodo.13845689

[17] "Behaviour (JADE v4.6.0 API)," *Tilab.com*, Dec. 02, 2022. https://jade.tilab.com/doc/api/jade/core/behaviours/Behaviour.html (accessed Dec. 01, 2025).

[18] S. Bhunia, A. Ferrando, V. Mascardi, and C. Vitale, "MAiS: Exploiting JADE as a multi-agent simulator of the immune system," in *Multi-Agent Systems: 21st European Conference, EUMAS 2024, Proceedings*, Dublin, Ireland, 2024, pp. 3–20, doi: 10.1007/978-3-031-93930-3_1.

[19] de Silva, L., Meneguzzi, F., & Logan, B. "BDI Agent Architectures: A Survey", in Proceedings of IJCAI-PRICAI, 2020. https://doi.org/10.24963/ijcai.2020/684

[20] Alexandre Yukio Ichida and Felipe Meneguzzi. 2023. Modeling a Conversational Agent using BDI Framework. In The 38th ACM/SIGAPP Symposium on Applied Computing (SAC '23), March 27-March 31, 2023, Tallinn, Estonia. ACM, New York, NY, USA, Article 4, 8 pages. https://doi.org/10.1145/3555776.3577657

[21] F. Taillandier, P. Di Maiolo, P. Taillandier, C. Jacquenod, L. Rauscher-Lauranceau, and R. Mehdizadeh, "An agent-based model to simulate inhabitants' behavior during a flood event," International Journal of Disaster Risk Reduction, vol. 64, p. 102503, Oct. 2021, doi: https://doi.org/10.1016/j.ijdrr.2021.102503

[22] C. Adam and B. Gaudou, "BDI agents in social simulations: a survey," The Knowledge Engineering Review, vol. 31, no. 3, pp. 207–238, Jun. 2016, doi: https://doi.org/10.1017/S0269888916000096

[23] "Architecture BDI", Politechnica University of Bucharest, 2002. https://turing.cs.pub.ro/auf2/html/chapters/chapter2/chapter_2_2_2.html (accessed Dec. 01, 2025).

[24] M. Wooldridge, *Reasoning About Rational Agents*. Cambridge, MA, USA: MIT Press, 2000, ISBN: 0-262-23213-8.

[25] S. Leask, "GROVE: A Computationally Grounded Model for Rational Intention Revision," Ph.D. dissertation, School Comput. Sci., Univ. Nottingham, Nottingham, U.K., 2021.

[26] M. J. Wooldridge, *An Introduction to Multiagent Systems*, 2nd ed. Chichester, U.K.: John Wiley & Sons, 2002.

[27] M. T. Robinson, "How Rare is Your Personality Type?," *Careerplanner.com*, 2018. https://www.careerplanner.com/MB2/TypeInPopulation.cfm (accessed Dec. 01, 2025).

[28] "World Personality Map — Country Personality Profiles — 16Personalities," *www.16personalities.com*. https://www.16personalities.com/country-profiles/global/world (accessed Dec. 01, 2025).

[29] "Myers Briggs Statistics: The 16 Personality Types," *Crown Counseling*, Nov. 26, 2024. https://crowncounseling.com/statistics/myers-briggs/ (accessed Dec. 01, 2025).

[30] Salvit, J., Sklar, E., "Toward a Myers-Briggs Type Indicator Model of Agent Behavior in Multiagent Teams," In: Bosse, T., Geller, A., Jonker, C.M. (eds) Multi-Agent-Based Simulation XI. Lecture Notes in Computer Science(), vol 6532. Springer, Berlin, Heidelberg. 2010, https://doi.org/10.1007/978-3-642-18345-4_3

[31] S. D. Date, ”Deriving mbti personalities in multi-agent systems,” M.S. thesis, Dept. Comput. Sci., Univ. Maryland, College Park, MD, USA, 2022.

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