A Multi-Agent organizational modeling at the backend of a metaversity

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Abstract. *Advances on Artificial Intelligence (AI) have inspired the design of innovative applications for education. However, its poorly planned use has led to a number of pitfalls mapped in literature, along with recommendations towards responsible AI. We are currently investigating how Multi-Agent Systems (MAS) can enhance higher education. In this paper, we introduce a MAS organizational modeling of typical campus, at the backend of a decentralized metaverse platform. The model is proposed to be scalable and refinable, such as to fit specific requirements of institutions eventually reusing it, and serve as a sand-box for teaching/research AI for education (and education for AI). Model dissemination and instantiation should provide empirical evidence for further analysis.*

1. Introduction

Multi-Agent Systems (MAS) have been exploited in the design of educational environments for at least three decades. From the perspective of Microworlds, the modeling for learning approach is undertaken since the 1990s in the NetLogo project [Wilensky 1999], a Multi-Agent programmable modeling environment, used by a large number of students, teachers, and researchers worldwide [Bazzanella et al. 2024]. From the dual perspective of Intelligent Tutoring Systems (ITS), early work proposed to support the development of ITS by decomposing the domain contents throughout the society of interactive and cooperative agents [de Barros Costa et al. 1995]. Other significant works also appear in the infancy of the ITS literature, e.g. [Giraffa et al. 1998], which rely on a MAS architecture as the foundation of a game-based learning environment.

The MAS approach persisted in benefiting the design of systems for human learning across the 2000s. In order to address the limited adaptability of distance learning platforms so available, and aiming at the improvement of HR qualification programs, a MAS framework is introduced along with a testbed tutor in [Silveira and Vicari 2002].

In [Bez et al. 2012], the authors introduce the use of influence diagrams for supporting the decision making of a mediator agent within a MAS. Such decisions include the choice of pedagogical strategies in order to guide health care practitioners. In a highlight from one decade later, in [Behr et al. 2022], the MAS approach is exploited to improve the search for Learning Objects (LOs), which might be compromised due to poor metadata completion. The active perspective of an LO designed as an agent, along with its communicative skills within the society, is supposed to result in a better quality of the recommendations provided by the LO repository.

Also towards the improvement of LO recommendation based on MAS, in [Mohamedhen et al. 2024] the authors propose an integration of this approach with deep learning advanced techniques in order to fit learner's knowledge levels and learning styles. Indeed, the large amount of data available online to the learner nowadays, together with scientific and technological advances allowing this amount of data to get processed, has led to an exponential appearance of LLM proposals for educational ecosystems. In [Chu et al. 2025] the authors review the literature on LLM agents applied to education, covering at about 250 primary studies within a period of 2 years.

This current landscape of educational ecosystems, in which individual entities are designed to deal with a large amount of data, suggests a new plateau of possibilities and challenges for the MAS approach. The need for synergic communication among these innovative entities on behalf of a (collective) shared goal, eventually yet tacit, has been resulting in original approaches such as LLM powered MAS for education [Li et al. 2024].

However, from the viewpoint of technology adoption and some already mapped impacts as a consequence, a number of researchers, societal representatives, and policy makers are currently lifting a number of concerns. For instance, in [Hooshyar et al. 2025], the authors elaborate on 9 critical issues regarding "fairness, transparency, and effectiveness of current AI methods and applications in education".

In order to address such concerns, we are currently investigating how the MAS approach might benefit the governance of incoming technologies within educational institutions, specifically higher education ones, according to their typical organizational levels while using these technologies. In this paper, we introduce the Agent-Group-Role organizational modeling of a Multi-Agent society, as an abstraction of some well-known active and interactive elements from campus. The proposed MAS takes place at the backend of a decentralized metaverse platform, through which learners are invited to interact both with their companion and other people's avatars.

The expected contribution is two-fold. On the one hand, the model is proposed to be scalable and refinable, such as to fit specific requirements of institutions eventually reusing it, while its instantiation might serve as a sand-box for teaching and research AI for education (and education for AI). Scalability would stand for the possibility of capturing other organizational units than the ones appearing in the proposed model, as well as increasing the agents communication language. Refinability might stand for determining a specific approach to the design of individual agents, e.g. BDI. On the other hand, the backend might ground innovative connectivity among campuses through the suggested frontend or another one.

This paper is organized as follows. In Section 2, we describe the main underpinnings of the model, which is introduced in Section 3. Section 4 closes the paper.

2. Theoretical foundations for the backend of a metaversity

Hereafter we describe some of the main pillars over which we build the proposed model.

2.1. On Technology-Enhanced Learning

In recent years, there have been increasing reports from around the world about the exploration of metaverse environments for learning [Lin et al. 2022, Wang et al. 2022, Han et al. 2023], notably for higher education [Ruwodo et al. 2022, Hassanzadeh 2022]. The educational ecosystem being designed in our current RD&I project is based on the concept of *metaversity* [Sutikno and Aisyahrani 2023] and its developments [Lee et al. 2024, Laurens-Arredondo 2024], with the aim of providing both traditional and innovative campus services through a decentralized metaverse environment.

According to previous work from our teams [Nóbrega et al. 2024], each learner within the metaversity may adopt one *pet* to act like a companion. The idea of a pet follows the criteria from the virtual characters proposed in the DynaLearn project [Wißner et al. 2012], such as affective appeal, ecology, moderated expectations regarding linguistic abilities, and so on. The pet is then a conversational agent aware of the learner's lifelong educational pathway, within their formal, non-formal, and informal contexts.

In addition to the attractive aspects, conversational AI-agents with appropriate design have proven suitable for promoting learning benefits [Lane and Schroeder 2022, Johnson and Lester 2018]. However, designers of learning companions are now challenged to take advantage of AI's state-of-the-art in order to propose accurate handling of large data amount. In addition, social ability is suitable for such entities, allowing them to engage in interactions not only with the learner but also with artificial peers in the society.

2.2. The adopted MAS approach: AGR meta-model

The MAS being introduced in this paper is a complementary part of the whole ecosystem. If one considers the purpose itself of providing novel benefits to the campus community, in order to transcend the traditional formal context, and accounting for responsible IT governance, so a model of the overall structure might be of significant support. Beyond education, the relevance of organizational modeling for management purposes is evidenced in a variety of other fields, for instance, to address problem solving related to hydric resources [Born et al. 2023].

The organizational modeling of the metaversity introduced in Section 3 relies on the Agent, Groups, and Roles (AGR) meta-model [Ferber et al. 2003]. The associations between the core concepts are illustrated in Figure 1(a), from [Roussille et al. 2021].

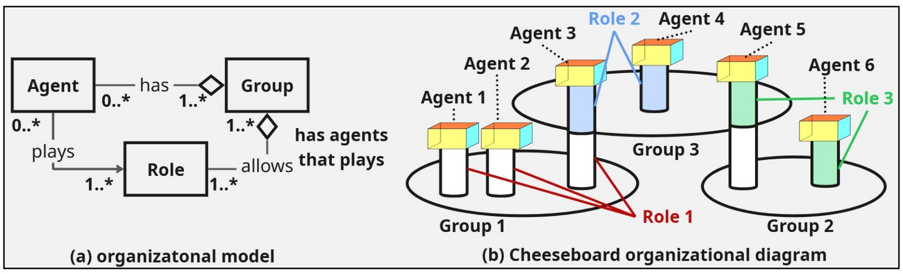

Figure 1. AGR representations: conceptual model (a) and cheeseboard diagram (b) [Roussille et al. 2021] (adapted).

An Agent is a member of one or more Groups. Therefore, a group is an atomic set of agent aggregation. In a formal specification, a group is described by a group structure, represented as a tuple S = <R, G, L>. This structure identifies all roles (R) and interactions (G) that occur within a group. The formalism for the individual interaction definitions is oriented by the interaction language (L). In summary:

- R: represents a set of all roles that can be played by agents while acting in a group;
- G: represents an oriented graph of valid interactions between two roles; Each edge of the graph receives a "label", indicating that a given role (r_i) initiates the interaction, named "label", with another role (r_j);
- L: represents the interaction language, which guides each interaction specified in the graph.

AGR models may be directly implemented at the MaDKit[1] platform, which allows the management of agents life cycle. This is particularly convenient if one intends to carry out model analyses from simulations.

The AGR model has been exploited in order to specify social normative behavior [Chebout et al. 2023]. This work is quite interesting because it deals with heterogeneous or even unspecified agent architectures. Therefore, unknown agents can freely join or leave the system, and interactions cannot be managed as they would in a predictive system. The authors agree on the use of the AGR model, improved to deal with these uncertainties.

3. Organizational modeling for a metaversity

Let us imagine a situation in which the learner is supported by an artificial assistant who accompanies them throughout their academic journey. The behavior of this assistant conforms to the AGR meta-model and may be technically defined from a relational pedagogical agent, provided with knowledge about the person being assisted, which has three distinct roles to carry out its objectives. These roles, depicted in Fig. 2, are independent entities that communicate and reason on a neuro-symbolic model, while at the same time giving the person being assisted the feeling of interacting with a single assistant agent.

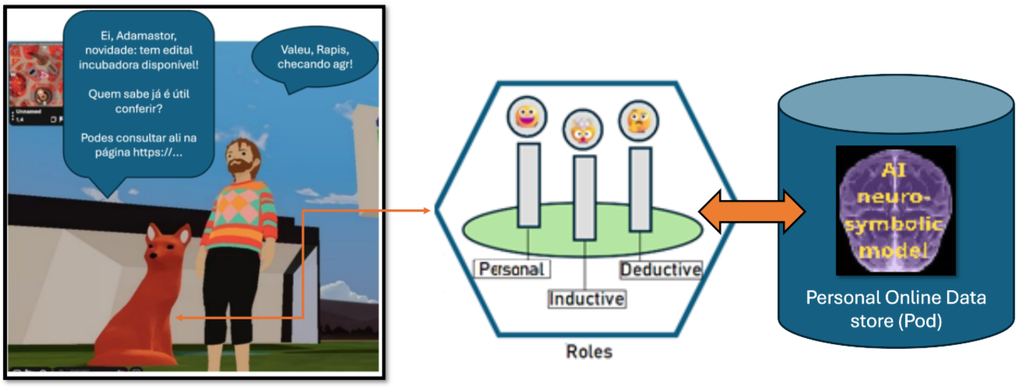

Figure 2. Roles identified for the companion (adapted from [Nóbrega et al. 2024]).

Hybrid approaches for modeling the learner's profile or preferences have proven suitable in early [Hasibuan and Nugroho 2016] and recent works [Nkambou et al. 2023]. In addition to allowing predictability and thus providing more accurate personalization, contemporary needs of explainability become crucial to achieve transparency and trust toward a responsible AI for education [Hooshyar et al. 2025]. On the other hand, as ensuring own control of personal data has been also contributing to reach reliability in Web

[1] https://www.madkit.net

applications in general [Mansour et al. 2016], we are adopting this approach for educational applications in particular. Indeed, both symbolic [Slabbinck et al. 2023] and neural large models [Ottenheimer 2025] have recently been considered to persist in Personal Online Data stores (Pods), with access provided by agent entities.

The roles identified for instantiating the entities include: (i) a personal agent, conceived as a natural language processor or even a ChatBot; (ii) a deductive knowledge agent, capable of answering queries based on specialized knowledge repositories, and (iii) an inductive learner agent, equipped with machine learning mechanisms for the purpose of updating knowledge (Fig. 2).

The vision of the triad of agents and their primary essential functionalities can be perceived at various levels (or groups), composing a dynamic in which the role played by the representative agent is distinct. In this way, we propose an Organizational Modeling of the community of agents in which the levels represent not only the learner, but also other conceptual instances of the university context, as illustrated in Fig. 3.

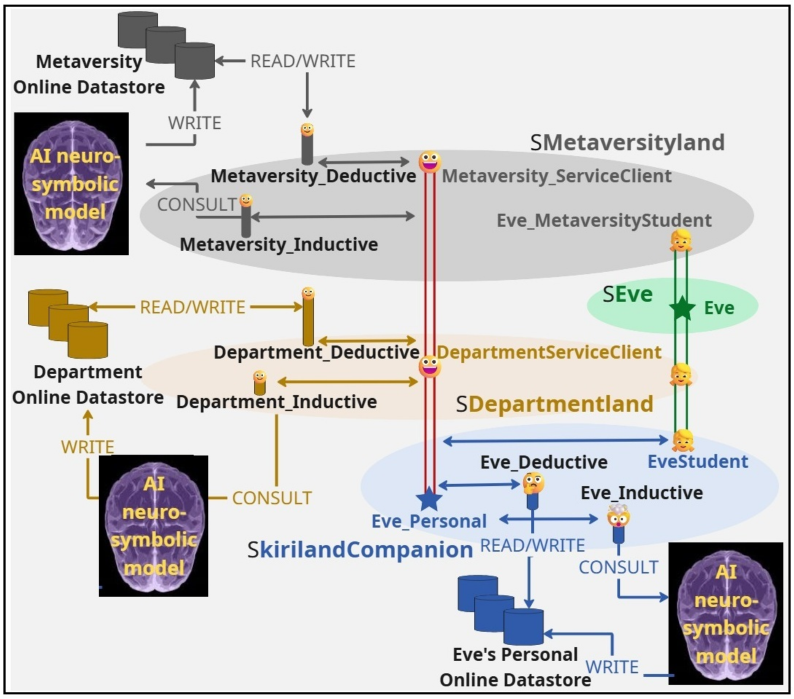

Figure 3. AGR cheeseboards for representing a metaversity.

In fact, we propose an Organizational Structure considering Eve as a Student at Metaversityland level, but there are other groups/levels, each with their respective inductive and deductive agents (and their technological apparatus) interacting with the Personal Agent. In turn, Personal Agent has the characteristic of transversality, being able to switch between the levels presented according to the situation. In other words, it is possible to transverse the SEve's roles to the levels above (e.g. Department), but we opted for customized returns to Eve through SKiriland's levels.

In this model, the deductive agent is responsible for querying the knowledge bases of the level to which it is associated. Similarly, the inductive agent queries AI Neurosymbolic Model to infer results, but also updates the knowledge base of its level.

All the groups' databases form a decentralized knowledge base whose parts are visible and accessible only to the agents in the respective group. For example, the contents of the decentralized base can be Eve's lifelong personal information, such as interests and likes, but they can also be documents such as regulations, resolutions and manuals that contain relevant information at the Department level.

Likewise, the AI Neuro-symbolic Models of each level include specialized knowledge, according to the level/group with which it is associated. Therefore, the training base and models of each Model may vary between the different levels/groups represented.

It is possible to transverse the SEve's roles to the levels above (e.g. Department), but we opted for customized returns to Eve through SKiriland's levels; (b) Eve's lifelong information (e.g. likes, interests) can be used as inputs for these databases; (c) University documents that clarify various subjects (e.g. regulations, resolutions, manuals) can be used as inputs for these databases; (d) Department documents that clarify various subjects (e.g. regulations, resolutions, manuals) can be used as inputs for these databases.

The groups/levels are:

- **SEve**: group that represents, in this scenario, Eve and her interface agent. Eve corresponds to a young woman, who has desires, goals and also doubts about her academic and professional background. Her interface agent, modeled as EveGuiResponsible, assists Eve in her first contact with this immersive environment, guided by software agents and Artificial Intelligence resources.
- **SKirilandCompanion**: group, in which Eve is represented as a student, EveStudent. This student is assisted by software agents that can assume three roles. In this case, the roles are Personal, DeductiveResponsible and InductiveResponsible. The agent that assumes the role Personal interacts directly with the student Eve, who is represented by an avatar. The agent that assumes the role DeductiveResponsible will be responsible for handling Eve's questions, received by Personal, using a deductive approach. Thus, DeductiveResponsible consults Eve's Pod, and returns about the student Eve's questions using a deductive approach. This approach takes into account information about Eve, such as likes and interests, personalizing the returns. The agent that assumes the role InductiveResponsible will be responsible for handling Eve's questions, also received by Personal, using an inductive approach. The InductiveResponsible consults an Artificial Intelligence Platform and returns about the student Eve's questions using an inductive approach. This approach takes into account information from Eve, specified using LLMs. This input specification allows to perform a supervised pre-training of the Neural Network, avoiding the typical "cold start" problem. Subsequently, new fine-tuning and optimizations occur, generating other LLMs. When the result of this analysis is returned, there is greater added value in this feedback. This can allow for even better support for Eve in her questions. In addition, it can also stimulate new Eve's interests.
- **SMetaversityland**: group that includes several roles. The intention is to represent the various nuances of a university or other educational institution. In this context, the agent that assumes the role Personal, from the SKirilandCompanion group, can also be a member of the SMetaversityland group, assuming the role MetaversityServiceClient. The idea is that several interactions will occur, using

specific Metaversity services. In addition, the returns, whether using the deductive or inductive approach, can be oriented to the Metaversity's particularities. Among these particularities, specific documents of this institution can be considered (e.g. regulations, resolutions, minutes, manuals). Thus, the Metaversity Online Datastore and the AI neuro-symbolic model of this group are specific to this context. In this case, the returns to Eve's questions, as a Metaversity's student, will be more suited to the Metaversity's particularities. We have more personalized returns, since we know about Eve's personal information, and the particularities of the Metaversity. Remembering that Eve's Pod is known by MetaversityServiceClient, which is basically the representation of the SKirilandCompanion's Personal.

- **SDepartmentland**: group that includes several roles. The idea is similar to what was explained for the SMetaversityland group. In the current group, the additional detail is the agent that assumes the Personal role, in the SKirilandCompanion group, can also be a member of the SDepartmentland group, assuming the DepartmentServiceClient role. Thus, the Department Online Datastore and the AI neuro-symbolic model of this group are specific to the Department's context. In this case, the returns to Eve's questions, as a department's student, will be more suited to the Department's particularities. We have more personalized returns, since we know about Eve's personal information, as well as the particularities of the Department. Eve's Pod is known by DepartmentServiceClient, which is basically the representation of the SKirilandCompanion's Personal.

In this context, for example, a software agent, belonging to the group SKirilandCompanion, can assume the role Personal and perform the inherent tasks associated with this role. If this software agent also belongs to the SMetaversityland group, it can assume the role MetaversityServiceClient. In this role, it is possible to interact with other agents by performing more personalized responses to Eve's questions. It offers a proper support, considering that the returns to her questions need to take into account the particularities of the institution where she is a student.

Possible scenarios within the MAS metaversity include:

3.1. Scenario 1: Horizontal interactions within Kiriland

In this scenario, we will illustrate a dialog situation between agents. The behavior of the agents and the flow of messages are described in Fig. 4. In this case Eve, as a student at KirilandCompanion, is curious about something involving Adam (e.g., *Has Adam ever done a Supervised Internship?* or *Did Adam like the Company he interned at?*). In this context, Eve, in the real world, is represented by EveStudent, at KirilandCompanion, being an Avatar.

1. EveStudent asks EvePersonal something about Adam (*1. Question about Adam*).
2. EvePersonal does not know about Adam, but knows who does, which is AdamPersonal (*2. I Know Who Knows*).
3. AdamPersonal queries AdamDeductiveResponsible, who can find out about Adam by consulting Adam's personal online data store (*3. Query about Adam*).
4. AdamPersonal receives feedback about Adam (*4. Return About Adam*).
5. AdamPersonal is aware of the feedback about Adam. Thus, this agent informs EvePersonal. Now, EvePersonal knows about Adam (*5. Now, I know*).

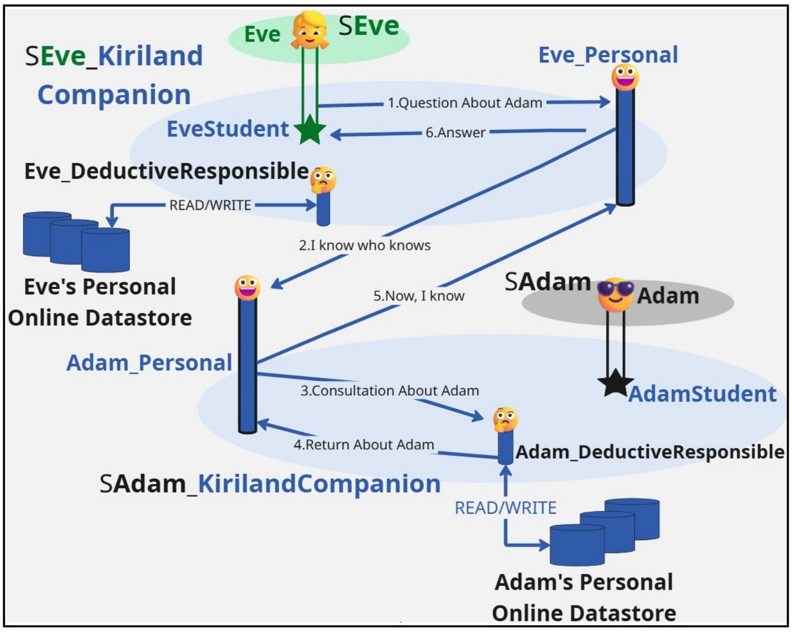

Figure 4. Dialogue between agents Eve and Adam.

6. Finally, EvePersonal informs EveStudent (*6. Answer*).

It is important to note that the mechanism for understanding Eve's question involves Adam's personal agent (AdamPersonal), as well as Adam's deductive agent (AdamDeductiveResponsible) and the information stored in Adam's personal online data store. Here, in order for Adam's personal information to be shared with Eve, Adam has previously made clear his policies for sharing with third parties and who are the third parties authorized to access his profile. This is established in a smart contract [Bartoletti et al. 2025], which is guided by the concept of sovereignty identity [Babel et al. 2025].

3.2. Scenario 2: Vertical interactions Kiriland $< - >$ Department

In this scenario, there is evidence of the transversality of the Personal who navigates and assumes the role back in the department (which is of a higher level) to get more specific information (Fig. 5). In this context, Eve asks about some information regarding the department she is studying in. In turn, the Personal takes on the role of DepartmentServiceClient in order to interact with agents at the Department level.

1. EveStudent asks Eve Personal something about the department (*1. Question about the department*).
2. EvePersonal knows who knows and, to do so, takes on another role (DepartmentServiceClient) (*2. I Know Who Knows but I have to assume another role…*)
3. Now EvePersonal is a DepartmentServiceClient.
4. DepartmentServiceClient queries DepartmentDeductive (*4. Consultation about the Department*).
5. DeductiveDepartment queries the Department on-line datastore and informs DepartmentServiceClient (*5. Return about the department*).
6. DepartmentServiceClient becomes EvePersonal and informs EveStudent (*6.Answer*).

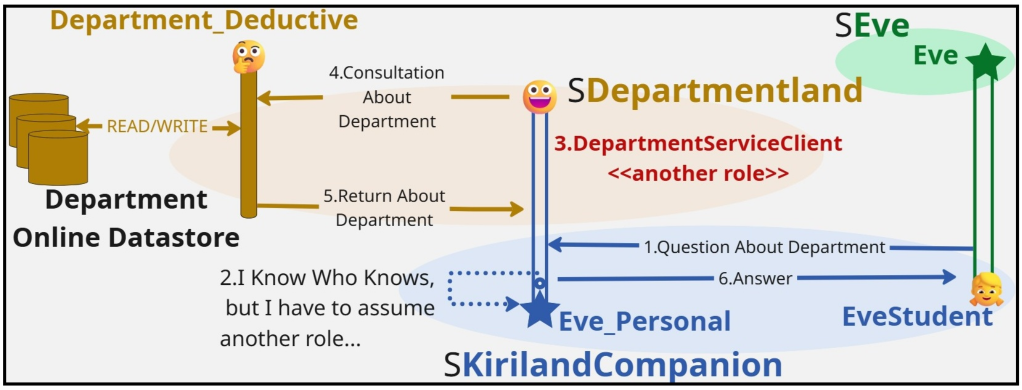

Figure 5. Personal in transversal mode, interacting with the department.

3.3. Scenario 3: Using Artificial Intelligence with AI Neuro-symbolic Models

In this scenario, Fig. 6, we consider a question from Eve that is not answered by EveDeductiveResponsible. When querying EveInductiveResponsible, AI neuro-symbolic models are used to provide a more coherent response to Eve's question.

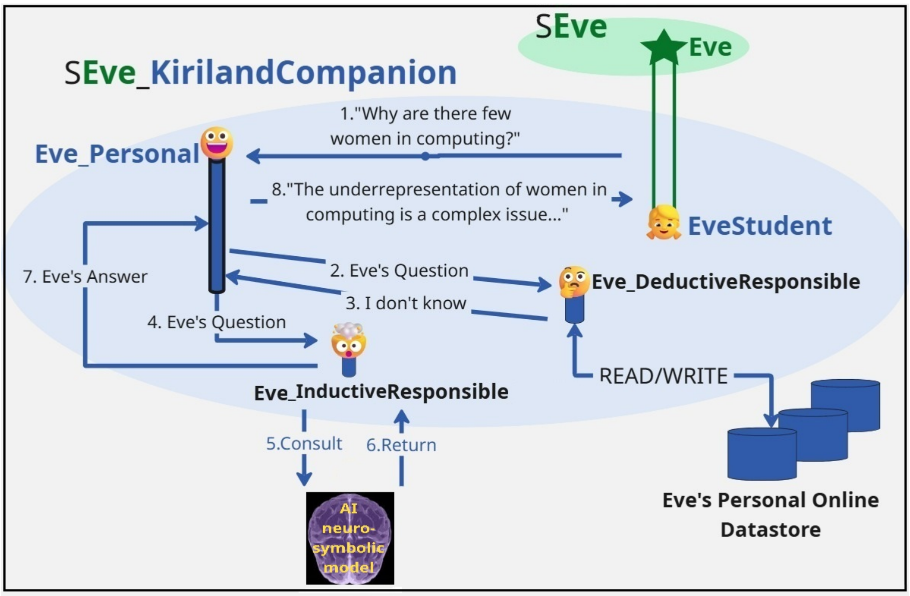

Figure 6. Using Artificial Intelligence with AI neuro-symbolic models.

1. Eve asks EvePersonal (*1. Why are there few women in computing?*).
2. EvePersonal consults EveDeductiveResponsible (*2. Eve's Question*).
3. Eve DeductiveResponsible does not know how to answer (*3. I don't know*).
4. Therefore, EvePersonal consults EveInductiveResponsible (*4. Eve's Question*).
5. Eve InductiveResponsible consults the AI neuro-symbolic model by using LLM and Eve's question "Why are there few women in computing?" (*5. Consult*).
6. EveInductiveResponsible receives the return from AI neuro-symbolic model (*6. Return*).
7. EveInductiveResponsible informs EvePersonal (*7. Eve's Answer*).
8. Finally, EvePersonal returns to Eve (*8. "The underrepresentation of women in computing is a complex issue..."*).

4. Conclusion

This paper proposes a Multi-Agent System (MAS) to provide university students with personalized, specific support that transcends the limits of formal education throughout their campus lifelong. The proposed MAS, under the form of Agent-Group-Role organizational modeling, is synergic designed to function with a decentralized metaverse environment as its frontend.

The model is proposed to be scalable and refinable, such as to fit specific requirements of institutions eventually reusing it, while its instantiation might serve as a sandbox for teaching and research AI for education (and education for AI). Also, the backend might ground innovative connectivity among campuses, through the suggested frontend or other one. Further work include model simulations within the MaDKit platform, and future deployments should provide empirical evidence for analyses and improvements.

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