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A Design Framework for Developing Advanced and Intelligent Learning Ecosystems

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Abstract

The ongoing transformation of education around the world aims at personalized, predictive, participative learning methods, supported by technology. It considers individual socio-economic status, conditions, and dispositions in personal, social, and behavioral contexts. Such a transformation requires the deployment of advanced technologies including artificial intelligence for providing a consistent representation and mapping between the different disciplines, methodologies, perspectives, intentions, languages, etc., as philosophy or cognitive sciences. This paper describes related challenges and solutions related to this transformation of learning ecosystems resulting in a formal reference architecture. This reference architecture provides an architecture-centric and policy-driven framework for designing and managing intelligent learning ecosystems in particular.

Keywords: *ML, algorithms, AI, software design, AI audit, evaluation frameworks*

1. Introduction

An ecosystem is the structural and functional unit of ecology where the living organisms interact with each other and their surrounding environment. It is the community of living organisms in conjunction with non-living components of their environment, interacting as a system [3].

When it comes to designing, managing, and implementing learning ecosystems, one needs to take into account not only mobile, technologies, big data and analytics, virtual reality, learning algorithms but also new computing technologies such as cloud, cognitive, and edge computing. Furthermore, there is a need for appropriate policies and governance schemes to be in place to control the system's behavior.

This paper explores the transformation of learning ecosystems using the Barendregt Cube [10]. Building such a framework requires cooperation of many different and sovereign stakeholders from different policy domains in a multi-disciplinary approach including learning sciences, engineering, but also social sciences.

The challenge is the understanding and the formal as well as consistent representation of the world of sciences and practices, i.e., of multi-disciplinary and dynamic systems in variable context, for enabling mapping between the different disciplines, methodologies, perspectives, intentions, languages, etc., as philosophy or cognitive sciences do.

Such a cooperation necessitates the advancement of communication and cooperation among the business actors from different domains with their specific objectives and perspectives from data level (data sharing) to concept/knowledge level (knowledge sharing). Thereby, it is essential to recognize different methodologies, terminologies/ontologies, education, skills, and experiences used in these different domains.

We must also keep in mind that we cannot decide on the correct integration and interoperability at data level without the use of case-specific context, objectives, or constraints. Instead, we shall do this at the real-world business system level.

2. Review of Existing Work

The Merriam-Webster Online Dictionary defines knowledge as "the sum of what is known: the body of truth, information, and principles acquired by mankind" [15].

According to Davenport et al., knowledge is "information combined with experience, context, interpretation, and reflection. It is a high-value form of information that is ready to apply to decisions and actions" [16].

There are different knowledge classes such as the following:

- Classification-based knowledge;
- Decision-oriented knowledge;
- Descriptive knowledge;
- Procedural knowledge;
- Reasoning knowledge;
- Assimilative knowledge.

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Knowledge can be represented at different levels of abstraction and expressivity, ranging from implicit knowledge (tacit knowledge) up to fully explicit knowledge representation, i.e., from natural language up to universal logic, using different ontology types as seen in Figure 1.

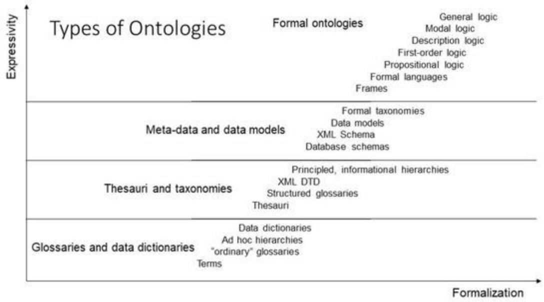

Figure 1. Ontology types

From the modeling perspective, three levels of knowledge representation are distinguished and must be consecutively processed:

- Epistemological level (domain-specific modeling)
- Notation level (formalization, concept representation)
- Processing level (computational, implementations)

Thereby, a model is defined as a representation of objects, properties, relations, and interactions of a domain, enabling rational and active business in the represented domain.

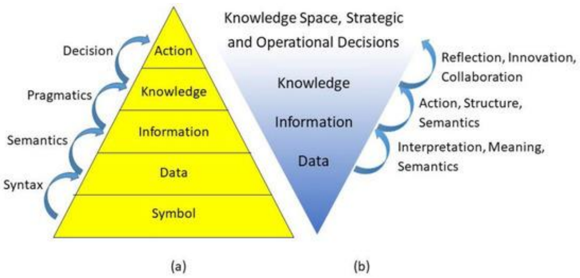

Figure 2. Knowledge pyramid (a) and model hierarchy (b)

The dynamics of knowledge creation, especially the importance of tacit knowledge and its conversion into explicit knowledge, have been analyzed by Nonaka and Takeuchi [20]. The process of converting tacit knowledge into explicit concepts through the use of abstractions, metaphors, analogies, or models is called externalization. Any business system can be represented using information and communication technology (ICT) ontologies.

The justification of the correctness and completeness of structure and behavior of the represented ecosystem includes the representational components, their underlying concepts, their relations, as well as the related constraints. For this purpose, various value-sensitive approaches can be considered. To name a few, VSD(Value-sensitive-design) and DfV(Design for Value) aspire to consider and integrate values from the design stage of a technological system or artefact.

VSD relates to values in two ways: acknowledging that technological design impacts our understanding of human values and focusing on how values can be inscribed in technological artefacts via design (Manders-Huits, 2011). The term "value" was defined in this context as "what a person or group of people consider important in life" (Friedman et al. 2006, p. 349), and is seen as guiding behaviors.

Verbeek (2006) further expands the theoretical tenets of VSD to address the influence of technologies on human actions through what scholars call *scripts*. These are prescriptions of how to act that are built into an artefact, thus charging technologies with morality.

On the other hand, DfV champions an "active value-driven steering of and intervention in technological development," which would make obsolete the "societal opposition during implementation and adoption" of new technologies (Van den Hoven et al. 2015). As such, DfV is strongly linked with the ideal of responsible innovation in its ambition to "contribute to the success, acceptance, and acceptability of innovations" (Van den Hoven et al. 2015).

When it comes to the values typically included in VSD, Friedman and Kahn (2002, pp. 1187–1193) list a collection of twelve "human values with ethical import often implicated in system design," which includes *human welfare*, *ownership, and property*, *privacy*, *freedom from bias*, *universal usability*, *trust*, *autonomy*, *informed consent*, *accountability*, *courtesy*, *identity*, *calmness*, and *environmental sustainability*.

While VSD frameworks might seem well-positioned to account for societal preferences, they may do so in a misguided manner. Davis and Nathan (2015, p. 12) argue that VSD tacitly suggests that "designers *must* attend to values supported by theories of the right, which are obligatory, and *may* attend to values supported by theories of the good, which are discretionary."

Le Dantec et al. (2009) argue that the articulation of VSD methodologies does not support the active refinement of the value classification. This is particularly concerning given the industry, government, and academia's increased interest in AI ethics, which focuses on transparency, explainability, and trustworthiness (Balasubramaniam et al. 2022; Deloitte 2019; High-Level Expert Group on Artificial Intelligence 2019; European Commission, 2020).

Since in some situations, norms and norm systems are more accurate indicators than values of the behavior within and across cultural groups, a Norm Sensitive Design (NSD) framework would help to better identify and understand users based on what they *do collectively* rather than what they *believe individually*.

Norm Sensitive Design has concrete implications for design processes, placing greater emphasis on *product prototyping* and *participant observation*. Since norms are concerned with behaviors, behaviors would be of primary consideration in design processes and research methods.

NSD (Norm-sensitive design) calls for considering norms and norm systems when designing and implementing new technologies. Rather than focusing on values alone, technological design can benefit from engaging with cross-

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and inter-cultural ethics of technology to explore the nature of norms and norm psychology and its integration in design.

As demonstrated, highly complex, multidisciplinary, dynamic, transformed (i.e., knowledge-driven) learning systems must be represented and developed using a system-theoretical, architecture-centric, ontology-based, and policy-driven approach.

3. Conceptual Framework for Intelligent Learning Ecosystems

The Barendregt Cube approach provides system-theoretical and engineering principles by representing any ecosystem with its components, their functions, and relations in the tree dimensions (Figure 3.):

- The system's architectural perspective, representing the system's composition/decomposition or specialization/generalization;
- The system's domain perspective, representing the involved domains and their actors;
- The system's evolutionary or development perspective.

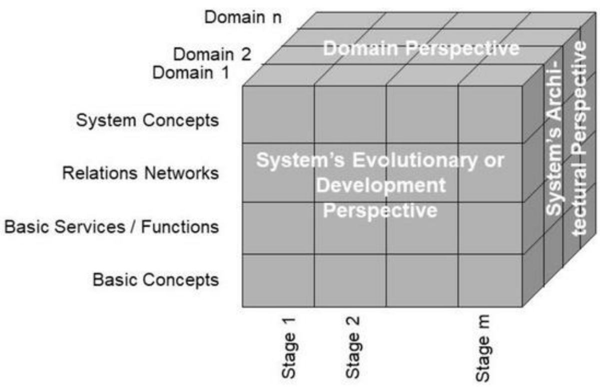

Figure 3. Generic model to represent ecosystems

As a starting point for designing and managing intelligent ecosystems, the concepts behind the domain-specific architectural components of the business system must be represented using domain-specific languages, ontologies, and methodologies. Global et al (2013) defined a policy ontology, as represented in Figure 4.

Next, the domains including the related actors involved in the business system use case must be defined. The ecosystem policy domain (4a) can be refined to consider specific aspects such as the legal policy, contextual policies, but also the service user's individual policy and the service provider's process-specific policy, as shown in 4b.

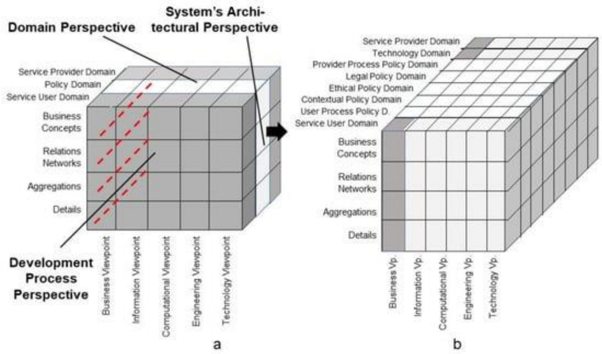

Figure 4. Refinement of the Policy Domain

Regarding the ethical policy domain, a norm-based approach can be implemented. Given that moral design has been identified among the goals of engineering education (Martin et al. 2021) and is part of the curricular content for teaching (Martin et al. 2020, 2023), these questions can also be used by instructors to prompt students' reflection about design ethics:

- Design question 1: Under which conditions does design prompt norm internalization within and across cultural groups?
- Design question 2: How are collective behaviors envisioned from the standpoint of technological designs?
- Design question 3: How does technological design affect societal norms of interaction and behavior?
- Design question 4: How can design alter the societal norms of interaction and behavior, and when this may constitute an overreach?
- Design question 5: What design processes and research methods can help better understand and predict user behaviors?

As a next step, sub-policy domains must be formally represented. This requires ontologies to represent the functionality or behavior of the ecosystem from the business as well as the security and privacy perspectives.
To formally represent security requirements of ecosystems, Souag et al. defined three main dimensions and related details:

- An organization with agents, assets, and locations;
- Risk with severity, threat incl. threat agent, attack method and tool, vulnerability, and impact;
- Treatment with security goals, requirements, criterion, and control.

As mentioned before, the establishment, management, and enforcement of an appropriate governance is inevitable to guarantee appropriate intentions and practices for developing and deploying advanced ecosystems regarding security, safety, and privacy. Those governance schemes must be properly and formally represented.

4. Conclusions

This paper addressed the challenges in designing and managing knowledge-based, policy-driven learning ecosystems. It provided a formal representation of knowledge spaces of contributing domains using approved ontologies, languages, and methodologies. For educational domains, there

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are several specialized sub-domain (disciplinary) ontologies. When such ontologies are missing, we can derive related ontologies from other top-level ontologies standards.

Innovations in science and technology can improve the delivery of learning, but they can also pose risks to global education system, e.g., by strengthening the digital divide between rich and low- and middle-income countries. As they are always bound to new social and digital challenges, objectives, basic principles, limitations, etc., must be carefully considered and defined in their economic, social, political, and environmental contexts.

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