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Design and development of integrations of the Digital Learning Environment to personalize and improve the training experience of UNITA students

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Design and development of integrations of the Digital Learning Environment to personalize and improve the training experience of UNITA students

Use of Learning Analytics techniques and Data-Driven Decision-Making strategies to personalize the Digital Learning Environment

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PhD Thesis

Contents

Abstract

The rapid and large-scale transition to online education triggered by the COVID-19 pandemic has accelerated the adoption of digital learning environments and highlighted the need for flexible, scalable, and learner-centered educational models. In this context, personalization has emerged as a key objective of contemporary digital education, particularly within higher education and lifelong learning scenarios. However, effective personalization requires not only technological solutions, but also robust design models capable of supporting alternative learning pathways while maintaining pedagogical coherence and comparability. This thesis proposes the *SPIRAL* model (Student-centered Personalization of Individual education through Reusable and Autonomous Learning units) as a macro-design framework for online courses and micro-credentials. The model is grounded in the formal structuring of learning outcomes and learning units, enabling the construction of multiple, alternative, and equivalent learning paths leading to the same educational goals. The research integrates natural language processing methods for semantic similarity, and graph-based representations to model relationships among learning outcomes and learning units. These representations enable the analysis of learning paths and support data-driven decision-making in course design and evaluation. The model is implemented and evaluated through applications in different educational contexts, including university courses, competence frameworks, and micro-credential ecosystems. The results demonstrate that the SPIRAL model provides a coherent and extensible approach to designing personalized learning pathways, supporting the identification of alternative routes toward learning outcomes and offering meaningful insights for instructional design and educational planning. The thesis contributes to the field of digital education by bridging instructional design, learning analytics, and personalization, and by providing a design-oriented framework that can inform the development and evaluation of learner-centred digital learning environments. The research also addresses needs that have emerged strongly within the UNITA European Alliance, where the use of digital learning environments plays a central role and the sharing of online

learning pathways represents one of the strategic priorities.

Chapter 1

Introduction

In recent years, educational systems have undergone a profound transformation, decisively accelerated by the COVID-19 pandemic. The health emergency imposed a sudden and large-scale transition toward online and distance learning modalities, involving institutions, educators, and students worldwide. This shift, which occurred within an extremely limited timeframe, represented an unprecedented event in terms of scale and impact, testing the capacity of educational systems to ensure continuity, quality, and inclusiveness of learning provision.

Although the initial adoption of online education was primarily a response to an emergency situation, over time the pandemic acted as a powerful catalyst for innovation processes that were already underway. Educators and learners were required to rapidly adapt to digital platforms and online learning environments, developing new competencies and redefining established teaching and learning practices. In this context, digital literacy emerged as a key prerequisite for active participation in educational processes, while e-learning demonstrated its potential to support flexibility, accessibility, and continuity of learning beyond the spatial and temporal constraints of traditional face-to-face education.

At the same time, the transition to online education led to significant investments in digital technologies and infrastructures, both at the institutional and individual levels. Universities and academic networks strengthened their digital learning environments by integrating tools for communication, assessment, and monitoring of learning processes. These investments contributed to consolidating digital education as a structural component of educational provision, fostering the widespread adoption of online and blended practices that persisted beyond the most critical phases of the pandemic.

During this period, educational practices oriented toward continuity of learning and student-centered approaches also emerged and were reinforced.

In particular, increased attention was devoted to learner-centered ecosystems capable of supporting flexible and adaptive learning pathways. Recent literature describes this evolution as an iterative cycle of visioning, planning, and implementation of learner-centered educational ecosystems, aligned with the broader paradigm of Education 4.0. Within this framework, personalized learning is identified as a key trend, alongside the meaningful integration of digital technologies and educational data.

Personalized learning can be understood as the possibility of adapting learning pathways, content, and instructional strategies to learners' characteristics, needs, and goals. In this perspective, approaches such as blended learning and flipped learning have gained increasing relevance, enabling a reorganization of learning activities across time and space. Allowing students to select content, courses, or alternative pathways, as well as to explore and develop their skills and competencies, represents a central objective of contemporary digital learning environments.

To effectively support personalization, course design plays a crucial role. Online courses aimed at personalization require a clear and coherent structure capable of accommodating different learning styles, learning paces, and individual preferences. This entails the adoption of adaptive learning technologies, diversified instructional methods, and flexible assessment strategies that can support multiple pathways leading to the same learning objectives.

Within this context, there is a growing need for shared design models that can guide educators in the development of online courses and foster collaboration among different stakeholders. At the same time, the increasing availability of data generated within digital learning environments offers new opportunities to analyze learning processes and to support evidence-informed design decisions. The integration of design models, learning analytics, and data-driven decision-making strategies thus represents one of the main challenges and opportunities of contemporary digital education.

This research is situated within this framework. The thesis proposes the *SPIRAL* model (Student-centered Personalization of Individual education through Reusable and Autonomous Learning units) as a macro-design model for online courses and micro-credentials. The model aims to support the personalization of learning pathways through a formal structuring of learning outcomes and learning units, enabling the definition of alternative and equivalent paths toward the same educational goals. By leveraging learning analytics techniques, graph-based representations, and data-driven approaches, this work investigates how the SPIRAL model can support the design, analysis, and improvement of digital learning environments. The research also addresses needs that have emerged strongly within the UNITA European Alliance, where the use of digital learning environments plays a central role and the sharing of online learning pathways represents one of the strategic priorities.

The thesis is organized as follows. **Chapter 2** introduces the research questions and objectives that guide the study, clarifying the direction of the investigation from the outset. **Chapter 3** presents a critical review of the state of the art on the main reference topics, including digital learning environments, instructional and learning design models, personalization strategies, and learning analytics. **Chapter 4** describes the SPIRAL model in detail, illustrating its core entities and relationships. **Chapter 5** outlines the adopted methodology, while **Chapter 6** and **Chapter 7** are dedicated to the application and evaluation of the model in different experimental contexts. Finally, **Chapter 8** summarizes the main results and discusses directions for future research.

Chapter 2

Research Questions and Goals

The decision to introduce the research questions at this early stage of the thesis, before the State of the Art, is intentional. The research questions have not only framed the overall research design, but have also actively guided the literature review process. Rather than emerging solely as a synthesis of existing studies, they have functioned as a lens through which the relevant bodies of literature were identified, analysed, and critically examined.

My research activity is situated at the intersection of Digital Learning Environments and Instructional Design. Over time, and progressively throughout my academic and professional career, the theme of learning personalization has become increasingly central. Initially approached as a pedagogical challenge within digital environments, personalization gradually emerged as a structural issue related to course design, learning outcomes formalization, and the representation of learning paths. This evolution led to the decision to pursue a research project specifically focused on the design and development of models that support personalization in a principled, scalable, and data-informed way.

Within this context, the following research questions have been defined.

> **RQ1** What personalization strategies are currently adopted in Digital Learning Environments, and what are their strengths and limitations? What elements are missing to make these strategies more effective?
>
> This question aims to provide a critical overview of existing personalization approaches in digital education. It focuses on identifying the main strategies proposed in the literature, such as adaptive learning systems, recommender systems, and analytics-driven interventions, while analysing their pedagogical assumptions, technological requirements, and practical constraints. Particular attention is devoted to understanding the limitations of current approaches and to identifying

conceptual or structural gaps that may hinder their effectiveness.

> **RQ2** To what extent semi-formal instructional design supports the personalization of learning paths by enabling multiple, equivalent routes toward the same learning outcomes?
>
> This question addresses the core contribution of the research. It investigates whether the formalization of learning outcomes, learning units, and their relationships, can effectively support personalization by allowing different learning paths to lead to the same target outcomes. The emphasis is on the concepts of equivalence, comparability, and the flexibility of learning routes, as opposed to an approach whereby adaptability is driven exclusively by the available data concerning learners.
>
> **RQ3** When studying graph-based representations of learning paths, which indicators can be considered to evaluate the design of learning paths, and how do these indicators vary across different levels?
>
> This question explores the analytical dimension of the research. By modelling learning paths as graphs at multiple levels (learning units, learning outcomes, and courses), it investigates which structural or semantic indicators can be defined to evaluate course design quality and also curricula design quality. The aim is to understand how such indicators behave at different levels of granularity and how they can support reflective and data-informed instructional design.
>
> **RQ4** What are the effects of formalised instructional design on student engagement, motivation, and progression within Digital Learning Environments?
>
> This question concerns the impact of the model on learners' experiences and outcomes. Although highly relevant, this research question is not directly addressed within the scope of the present thesis. As will be progressively clarified throughout the work, investigating these effects would require longitudinal studies, controlled experimental designs, and extensive empirical data collection. In retrospect, this objective proved to be overly ambitious for a single doctoral project. Nevertheless, the question remains an important direction for future research and is discussed as a potential extension of the work presented here.

Together, these research questions define a coherent research trajectory that moves from the analysis of existing personalization strategies, through the proposal and examination of a novel design model, to the exploration of analytical tools for evaluating learning path design. They provide the conceptual framework for the literature review presented in the following chapter and for the methodological choices discussed later in the thesis.

Chapter 3

State of the Art

Goals: The objective of this chapter is to construct a rigorous and coherent foundation for the research by analysing the state of the art in digital education and its associated domains. The chapter surveys the evolution of Digital Learning Environments (DLEs), examining their pedagogical roots, technological affordances, and their role in enabling personalized and student-centered learning. Special attention is devoted to the theoretical paradigms—such as behaviourism, cognitivism, constructivism, and sociocultural theories—that inform the design and implementation of digital ecosystems. Furthermore, the chapter investigates how instructional design models, learning design approaches, and modular structures such as microcredentials contribute to the flexibility, scalability, and personalization of learning pathways. The analysis includes both classic and contemporary models, highlighting the shift from static course structures to dynamic, data-driven, and competency-based learning architectures. An additional goal is to review the methodological and technological developments in adaptive learning, educational recommender systems, and learning analytics, emphasizing how these technologies support decision-making, learner modelling, and continuous improvement. The chapter also critically examines the ethical and governance challenges associated with data-intensive personalization, including issues related to privacy, transparency, algorithmic bias, and institutional responsibility. By synthesizing these dimensions, the chapter identifies gaps and opportunities in the existing literature and delineates the conceptual foundations necessary for the development of our proposition - the SPIRAL model.

3.1 Digital Education and Digital Learning environments

3.1.1 Digital Education: Definition, Historical Evolution and Technological Trends

Higher education has undergone a series of profound transformations as a result of digitalization, global disruptions, and changing societal demands. The integration of educational technology has redefined both traditional teaching processes and the roles of learners and educators. Digital education, also known as technology-enhanced learning or e-learning, represents a contemporary approach to education that harnesses the power of digital technologies to revolutionize and augment the learning experience. It encompasses a broad spectrum of applications, methodologies and tools aimed to integrating technology seamlessly into educational practices across various levels and disciplines. The trajectory of digital education's development reflects a progression from early forms of computer-assisted instruction to sophisticated, adaptive systems integrated with institutional ecosystems. Initially, digital platforms in higher education served primarily as repositories for static content, digitized lecture notes, reading lists, and rudimentary quizzes, which mirrored the structure of traditional teaching without fundamentally altering it. These first iterations relied heavily on behaviorist principles, where structured repetition and direct feedback dominated the instructional design. Over time, however, advances in computational capability and network infrastructure facilitated more interactive features, such as multimedia integration and branching pathways that responded to learner input [49]. Historical examination also reveals how large-scale external events, pandemics, shifts in socio-economic conditions, acted as accelerators for digital innovation. The sudden necessity for remote delivery during COVID-19 prompted widespread adoption of blended modalities that combined synchronous virtual classrooms with asynchronous self-paced modules [19]. This hybridization demanded improvements in both infrastructural robustness and pedagogical versatility. Institutions that had invested earlier in flexible learning environments found themselves better positioned to expand interactive capacity quickly, whereas those reliant on purely physical infrastructure experienced greater disruption.

This transition was catalyzed by advances in Learning Management Systems (LMS), big data analytics and adaptive learning technologies, all of which are now central to institutional strategies for course delivery and curriculum design [17]. Alongside these technological incorporations, institutions have been compelled to reconsider long-standing pedagogical models to better address diverse student populations and the varying contexts under which learning occurs. The shift towards digital environments has reinforced the movement from teacher-centered approaches towards models that permit greater learner agency. This dynamic is especially evident in competency-based education systems, where academic progression is contingent on demonstrable mastery rather than on standardised time frames [19]. Educators in such contexts are expected to combine technology-enabled resources with active learning strategies, such as project-based activities and collaborative online engagements, resulting in a fundamental change in their professional responsibilities and interactions with students. Adaptive learning emerged as a central trend, enabling course structures to shift dynamically according to individual performance profiles. Early adaptive systems often focused on single parameters like quiz scores or completion rates, but subsequent generations began incorporating multi-dimensional datasets including behavioral indicators and engagement metrics [17]. This pedagogical shift towards personalization and learner-centered models has created the conditions for the adoption of more advanced, data-driven technologies capable of supporting adaptive decision-making and scalable forms of individualized support within digital learning environments.

The complexity of these systems deepened further with the advent of artificial intelligence (AI), which introduced models capable of interpreting learners' cognitive states and recommending targeted interventions in real time [40]. These developments fundamentally altered the manner in which users interacted within the educational environment. Learners no longer merely consumed predetermined sequences; instead, they became an integral part of a continuous feedback loop between human agency and algorithmic suggestions.

For instance, AI-enabled virtual teaching assistants integrated with existing LMS platforms can provide immediate feedback loops and curated content updates based on ongoing performance profiles [38]. These systems depend heavily on interoperability standards that allow seamless communication between institutional infrastructures and emerging AI solutions. Despite the potential benefits, adoption is not without challenges. Many educators remain unfamiliar with the systematic processes required to integrate advanced technologies, such as generative AI tools, into micro-curricular design at scale [37]. The lack of training infrastructure limits experimentation with newer formats like massive virtual classrooms, where instructional design matrices (used to systematically align learning outcomes, activities, technologies, and assessment) can be applied for designing richer interactive experiences. This skills gap underscores an ongoing need for targeted professional development programs that bring pedagogical theory into alignment with technological capabilities. In this context, Personalized adaptive learning has emerged as a prominent paradigm for enhancing the quality of higher education experiences [37]. Parallel to personalization efforts, universities are exploring also flexible credentialing methods through microcredentials such as digital badges. These credentials can reside within competency-based platforms or as part of open badge ecosystems accessible across different services [2]. Such systems support diversified learning trajectories by allowing learners to demonstrate mastery across discrete competencies that could be recognized beyond the originating institution. While current implementations often require manual intervention from instructors or course designers to match badges to individualized pathways, emerging algorithms may eventually automate this process more effectively. Despite these advances, the integration of personalization within DLEs often remains implicit, fragmented, or driven primarily by platform-level affordances rather than by explicit instructional design models.

The confluence of immersive technologies, robotics, and AI also opens new possibilities for replicating practical scenarios digitally [40]. Higher education's integration with broader socio-economic systems implies preparing graduates not only for current markets but also for anticipated future shifts in work organization. Consequently, curricula must balance theoretical frameworks with simulated or augmented environments in which applied skills can be developed safely yet authentically. Technological interventions here are not confined to isolated courses; they ripple into programmatic designs as institutions recalibrate their offerings around new forms of digital literacy. Large-scale disruptions such as the COVID-19 pandemic accelerated certain trends but also highlighted vulnerabilities in existing educational systems. Emergency remote teaching served initially as an improvised response mechanism but later gave rise to innovations that questioned conventional delivery models [35]. Institutions began documenting context-specific practices to retain productive elements from this forced experiment while moving away from crisis-driven improvisation toward more intentional blended or hybrid modalities. Digital transformation has enabled combining synchronous classroom interaction with asynchronous resources globally accessible via online platforms [3]. Many courses now employ flipped classroom models where foundational knowledge is acquired individually before class time is reserved for application-oriented discussions or collaborative problem-solving activities. This blend promotes flexibility without discarding the social dimensions integral to learning communities. As research continues, there is an evident trend towards integrating multimodal datasets, academic records, behavioral metrics, self-reported confidence measures, into comprehensive learner profiles used by adaptive engines [17]. Such integration aims at improving recommendation precision for instructional content while allowing predictive analytics to intervene early when indicators suggest a risk of disengagement or failure. Nevertheless, concerns around data privacy, algorithmic bias, and equitable access must remain central considerations if these innovations are to enhance learning outcomes responsibly. Digital education in higher education thus represents a complex interplay between technology infrastructure, pedagogical design choices, evolving educator roles, credentialing mechanisms like badges, and socio-cultural adaptation processes triggered both by deliberate policy changes and external contingencies. The breadth of its scope suggests that future advancements will likely emerge from cross-disciplinary cooperation spanning education research, software engineering, psychology of learning, and institutional governance frameworks. An important milestone is the integration of explainable AI (XAI) into educational platforms [24]. Early adoption phases faced skepticism over opaque decision-making by complex models. XAI frameworks address this by making recommendations transparent, explaining why certain resources are suggested or why specific assessments are triggered, which increases trust among educators and students alike. Historically, this shift parallels broader ethical discourses around algorithmic accountability and data privacy in educational contexts. There has been persistent recognition that technological sophistication alone does not guarantee acceptance unless its operation can be rationalized clearly to stakeholders.

One influential strand in the evolution of digital education has been microcredentialsing technologies such as open digital badges. Initially introduced as virtual equivalents to paper certificates, these badges evolved into portable, verifiable records embedding metadata about competencies achieved. Their role in historical context intersects with broader modularization trends; instead of binding students to linear progression within degrees, microcredentials allow accumulation of discrete skills recognized across different platforms and employers. This marks a departure from monolithic qualification frameworks toward granular certification embedded directly within adaptive systems [2].

Technological trends have also encompassed advances in multimodal content formats and delivery methods [28].From text-based modules to immersive simulations and virtual laboratories, there is a notable expansion in representational diversity aimed at accommodating varied learning styles. In turn, this reflects theoretical influences described in the section 3.1.4, where constructivist and experiential approaches encouraged authentic context replication through technology-mediated experiences. Interactive case studies embedded within online modules replace passive reading with active problem-solving conditions akin to real-world scenarios. This ongoing diversification impacts instructional design models such as SPIRAL or modular approaches by encouraging iterative complexity layering aligned with learner readiness stages, moving away from rigid curricular orderings established at the course outset [49].

Learning analytics represent another pronounced trend in the evolution of digital education whose growth trajectory aligns closely with the development of adaptive technologies [19]. While initially used chiefly for retrospective analysis, such as end-of-term performance reports, they increasingly serve predictive functions aimed at preempting dropout risks or sustained underperformance. By aggregating datasets across cognitive measures, behavioral logs, and resource usage patterns, institutions can intervene earlier with personalized pathways or support services [17]. This expanding role has influenced how platforms store and process data, real-time computation capabilities are necessary for these feedback loops but remain constrained by trade-offs between computational intensity and granularity of insight [27]. The diversity of platforms themselves also marks an important historical shift [17]. No longer confined to monolithic institution-hosted systems, digital education now operates across interoperable ecosystems where LMS tools link seamlessly with external repositories, video conferencing services, gamified quiz engines, collaborative document editors, and credentialing databases. This distributed architecture introduces resilience by allowing redundancy across channels while broadening functional scope through specialized integrations, for instance, embedding natural language processing chatbots within existing courseware to provide conversational support [24]. As interoperability standards solidify further, such integrations promise smoother transitions for both learners navigating multiple environments and educators compiling cross-platform metrics into coherent analytic dashboards.

3.1.2 Theoretical Foundations and Pedagogical Paradigms

Educational technology's effectiveness in higher education depends not only on the sophistication of the platforms used, but also on the alignment of these tools with robust theoretical and pedagogical frameworks. Multiple learning theories contribute to shaping digital learning environments in ways that accommodate diverse cognitive processes and preferences.

Behaviorism, for instance, influences web-based instructional design by structuring activities into clear learning pathways supported by repetitive practice and immediate feedback mechanisms. This structured approach can encourage persistence for learners who benefit from reinforcement-driven progression models, yet it may be less adaptable for students who thrive on exploratory or self-directed methods.

Cognitivist perspectives bring attention to optimizing mental processing through techniques such as chunking of instructional content, integrating multimedia elements while managing cognitive load, and providing scaffolding to strengthen memory retention. These principles are especially relevant when deploying complex simulations or multi-layered problem-solving tasks in online platforms. Nevertheless, the calibration of these tools is imperative, as excessive information density or poorly timed scaffolds have the potential to overwhelm learners and hinder their ability to engage with the material.

Constructivism moves further towards learner agency by promoting inquiry-led approaches where students build their own understanding through active engagement. Digital environments offer varied ways to support this paradigm, such as project-based tasks within virtual laboratories or interactive case studies embedded in course modules. Yet without guiding structures, some learners may experience frustration or disengagement if left entirely to navigate complex domains unaided. *Social constructivist* principles add a collaborative dimension to this framework by situating knowledge creation within peer interaction, forums, group projects, and reciprocal feedback loops are common implementations. The efficacy of these communities depends on maintaining productive discourse and equitable participation among group members.

From a different vantage point, *connectivism* redefines how learners interact with knowledge networks, emphasizing that learning occurs through connections made across nodes of information and social relations. This is particularly suited to the massive scale of web-based instruction (WBI), where knowledge repositories exist beyond institutional boundaries. In practice, platforms grounded in connectivist principles may integrate automated resource recommendation systems that link learners with curated external datasets or specialist communities. While potentially enriching, this openness introduces questions about content reliability and contextual appropriateness.

Experiential learning maintains its relevance in digital contexts through simulated environments, virtual fieldwork exercises, or interactive role-playing scenarios. These designs hinge on cycles of concrete experience, reflective observation, abstract conceptualization, and active experimentation. *Situated learning* similarly emphasizes embedding instruction in authentic contexts that mirror real-world professional practices. For instance, virtual internships hosted within institutionally moderated spaces allow learners to participate in community-specific workflows before engaging with actual industries.

A nuanced theoretical architecture often integrates these perspectives instead of adhering strictly to a single paradigm. Goutam Mondal's proposed conceptual framework exemplifies such synthesis by layering foundational theory beneath design principles like interactivity, authenticity, feedback loops, reflection opportunities, and mechanisms for social engagement [34]. This multi-tiered model aims to guide designers in translating theoretical constructs into functional components for WBI systems. Each principle interacts dynamically; for example, authentic contexts often necessitate rich interactivity and reflective processing phases.

The shift towards personalized learning adds another dimension to theoretical considerations. Adaptive systems draw from constructivist notions of individualized exploration while leveraging behaviorist feedback models for rapid correction when trajectories deviate from desired competencies [17]. Data-driven adaptivity also echoes connectivist thought, systems dynamically source varied content streams based on learner profile analytics. Designers must be cautious here; overly rigid algorithmic personalization can constrain exposure to unexpected yet valuable perspectives.

Microcredentialsing frameworks like digital badges intersect directly with these paradigms [2]. When embedded thoughtfully within competency-based instruction informed by clear pedagogical theory, such credentials become more than simple markers, they act as narrative threads mapping a learner's progression through contextually meaningful experiences. In this way, badge-based pathways may manifest aspects of situated learning by representing achievements tied to real-world-relevant tasks. The emphasis on blending synchronous and asynchronous engagements also ties back to pedagogical foundations mentioned earlier. Blended models benefit from flexibility while maintaining human interaction's social constructivist benefits [19]. Active learning spaces derived from flipped classroom strategies exemplify how theory informs practice: pre-class preparation implements cognitive structuring; classroom application sessions foster collaborative construction of knowledge. Theory-guided technological integration thus appears likely to remain central for advancing digital education frameworks discussed in previous section.

Technological potential will inevitably depend on whether its deployment resonates with established principles of how humans learn effectively in mediated environments. In the absence of congruence between paradigms and platforms, efficiency gains are at risk of becoming superficial enhancements as opposed to substantive educational advancements. Designers' challenge lies both in respecting theoretical integrity and embracing adaptive innovation suited to emerging contexts, a balance that reshapes how institutions conceptualize teaching roles and learner experiences alike. Integrating these perspectives in real Digital Learning Environments requires explicit design artefacts that preserve pedagogical coherence across levels and contexts. In particular, such artefacts are needed to govern the tensions between learner agency and automated adaptation, and between exploratory learning and efficiency-oriented optimization.

3.1.3 Opportunities and Challenges in Digital Education

As highlighted in the previous sections, the expansion of digital education outlines a complex landscape in which technical expertise, pedagogical vision, and institutional readiness interact in heterogeneous ways. The main opportunities emerge from the ability of contemporary educational platforms to integrate advanced computational tools, such as artificial intelligence and machine learning, within instructional workflows. These technologies enable the processing of large volumes of data related to academic pathways, engagement levels, and assessment outcomes, translating them into interpretable profiles that support adaptive course recommendations and learning pathways [24].

This approach marks a significant shift from reactive instructional design toward predictive models capable of anticipating students' needs in near real time. Systematic data analysis allows for the early identification of signals of difficulty or disengagement, enabling timely and targeted interventions directly within the digital learning environment. In this context, generative artificial intelligence introduces an additional layer of personalization by automating content diversification. In scenarios characterized by large-scale participation and asynchronous delivery, AI systems can generate alternative explanations that emphasize different cognitive modalities (for instance, privileging visual representations or narrative-based approaches) thus expanding accessibility and reducing the burden of manual resource creation [37]. Similarly, these frameworks can support the dynamic updating of problem sets and instructional materials, ensuring curricular relevance in rapidly evolving disciplinary contexts.

Alongside these opportunities, however, significant structural challenges persist. Access to digital infrastructure represents a fundamental enabling condition: inequalities in broadband availability continue to limit full participation for large segments of the population, both in peripheral areas of technologically advanced countries and in resource-constrained regions globally [19]. Even open educational resources, despite their economic and reuse advantages, remain ineffective without minimal network access, making the reduction of the digital divide a prerequisite for any meaningful innovation strategy.

From a technological perspective, advanced adaptive frameworks—such as those based on deep reinforcement learning applied to educational contexts—demonstrate substantial potential to enhance personalization through the continuous integration of multimodal data, including textual input, audiovisual signals, and engagement indicators [36]. However, this level of complexity amplifies the challenges associated with the coherent processing of heterogeneous data, requiring models capable of preserving semantic consistency and operating in real time, with consequent implications for computational costs and institutional sustainability.

These dimensions are further compounded by ethical considerations. The use of predictive models built on extensive student data raises critical issues related to privacy, informed consent, and algorithmic transparency [24]. While explainable artificial intelligence approaches can partially mitigate these risks, a structural tension remains between interpretability and performance optimization. From a pedagogical standpoint, opportunities lie in designing digital environments that progressively balance challenge and support, fostering the development of problem-solving skills and resilience through authentic activities and simulations of professional contexts [36].

Finally, the costs associated with the development, maintenance, and continuous updating of AI-based systems represent an additional persistent concern, particularly for smaller institutions or those operating under limited public funding [28]. The selection of digital tools therefore requires careful consideration of usage contexts, infrastructural constraints, and instructional strategies, in order to avoid overengineered solutions misaligned with actual user needs. Within this framework, social interaction engineering and collaborative support mechanisms represent a promising area, provided that they are designed to foster meaningful and inclusive exchanges rather than gamification driven solely by activity metrics [34].

Taken together, these dimensions reveal a structural tension between the transformative potential and the operational risks of digital education. Effectively realizing the opportunities it offers requires coordinated action to bridge access gaps, embed ethical safeguards within algorithmic architectures, equip educators with advanced instructional design competencies, and ensure sustained institutional commitment to long-term operational excellence. These challenges highlight that the effectiveness of digital education does not depend solely on technological sophistication, but on the availability of explicit macro-design structures at the course level. Without clear formalization of learning outcomes, modular learning units, and their relationships within learning paths, adaptive technologies risk amplifying fragmentation instead of supporting coherent personalization.

3.1.4 Definitions and Conceptualizations of Digital Learning Environments

The term *Digital Learning Environment* (DLE) has been adopted in the literature with a variety of meanings, often reflecting the disciplinary background, pedagogical orientation, or technological focus of the authors employing it. At a general level, a DLE can be understood as a mediated space in which digital technologies support, structure, and extend educational processes. Early conceptualizations primarily emphasized the digitization and online delivery of instructional content, whereas more recent definitions highlight the dynamic interplay between technological infrastructures, pedagogical models, and data-driven decision-making processes [6].

Within this broader evolution, digital learning environments are increasingly framed as socio-technical systems rather than as mere platforms or repositories. They comprise hardware and software components, learning resources and activities, pedagogical strategies, and interaction patterns involving both human actors and algorithmic agents. From this perspective, the environment does not simply host learning activities but actively shapes them through feedback mechanisms, adaptive features, and analytics-informed interventions.

A prominent line of research conceptualizes DLEs as adaptive systems capable of responding to individual learner characteristics in real time. In such systems, adaptive learning technologies function simultaneously as interfaces for interaction and as engines for data processing, enabling the dynamic adjustment of content sequencing, pacing, and instructional pathways [2]. Personalization is thus treated not as an optional add-on, but as a core operational principle embedded in the design of the environment. Learning pathways generated within these systems differ from static course structures by evolving in response to learner performance, preferences, and, in some cases, affective variables [17].

Closely related definitions emphasize the role of continuous data collection and analytics-enabled feedback loops. In this view, digital learning environments are characterized by their capacity to monitor learning processes in an ongoing manner and to support pedagogical decisions beyond summative assessment [6]. Data streams originating from Learning Management Systems (LMS), behavioral tracking tools, and institutional information systems can be integrated into dashboards that provide actionable insights for both learners and educators [19]. The environment therefore operates as a decision-support framework, enabling instructional adjustments during the learning process instead of exclusively after its completion.

Other contributions foreground flexibility as a defining characteristic of DLEs, highlighting the possibility of learning across different times, spaces, modalities, and degrees of learner autonomy [50]. From this standpoint, a digital learning environment may encompass synchronous online lectures, asynchronous discussion forums, self-paced modular courses, or collaborative workspaces that dynamically group learners based on shared interests or goals [19]. The emphasis is placed on interoperability and on the coexistence of heterogeneous educational resources within a coherent pedagogical framework.

Additional conceptual layers emerge when considering purpose-built components such as micro-credentialing mechanisms integrated within digital environments. Through hierarchical badge systems, competency frameworks, and adaptive learning models [2], DLEs can support modular recognition of learning achievements without requiring the completion of full degree programmes. This reinforces the view of digital learning environments as modular architectures composed of interoperable elements that can be assembled into customized learning trajectories.

The experience of emergency remote teaching during the COVID-19 pandemic further expanded definitional boundaries. It highlighted the need for digital learning environments to ensure infrastructural robustness, scalability, and interoperability under conditions of disruption. Consequently, contemporary definitions increasingly incorporate preparedness for rapid shifts between modalities and for hybrid configurations that combine synchronous and asynchronous activities without substantial losses in quality or engagement.

Social interaction constitutes another central dimension in many definitions of DLEs. Frameworks informed by social constructivist theories regard collaborative affordances, peer interaction tools, and shared knowledge-building activities as essential components [31]. In this sense, digital learning environments are designed not only to transmit information, but also to mediate complex social processes that contribute directly to learning.

Institutional and strategic perspectives further influence how DLEs are conceptualized. In some contexts, they are framed as strategic assets embedded within broader organizational ecosystems, aligned with institutional missions related to access, inclusivity, quality assurance, and preparation for digitally mediated professional contexts [37]. Emerging technologies such as artificial intelligence extend these perspectives by enabling anticipatory and predictive functions, including recommendation systems, automated grouping of learners, and early identification of learning difficulties [19].

Despite this convergence, debate persists regarding the scope of the term. Some authors advocate restricting it to intentionally designed pedagogical platforms, while others argue that learners' self-assembled technological ecosystems—comprising messaging applications, cloud services, MOOCs, and social media—can functionally operate as digital learning environments. For reasons of analytical clarity and research comparability, formal definitions tend to favor the former approach [14], even while acknowledging the pedagogical relevance of the latter in practice.

Overall, the literature suggests that comprehensive definitions of digital learning environments must integrate at least three interrelated dimensions: the technological infrastructure, the pedagogical framework guiding design choices, and the socio-organizational context in which the environment is embedded. Omitting any of these dimensions risks oversimplifying how digital learning environments actually operate and how their potential benefits can be realized in practice [2]. Contemporary research thus moves away from a single, universal definition and instead points toward a family of conceptually aligned interpretations that capture the multifaceted nature of technology-mediated learning spaces.

The DELTA Research Group Definition of Digital Learning Environment

The concept of Digital Learning Environment has been progressively refined over several decades and has appeared in the literature under different terminologies, including *Virtual Learning Environments* [47], *Online Learning Environments* [29], *Computerized Learning Environments* [1], and, more recently, *Digital Learning Environments* [39]. As observed by Barana and Marchisio Conte [4], these terminological variations converge on a shared core idea: the use of Internet-based technologies to provide a structured context that supports learning processes, most commonly implemented through a Learning Management System (LMS).

According to Watson and Watson [45], an LMS can be described as an infrastructural system designed to deliver and manage instructional content, support the definition and assessment of learning objectives, monitor learner progress, and collect data to enable oversight and evaluation of the learning process. While initially conceived to support fully online education, LMS-based environments have also been shown to enhance and integrate face-to-face teaching practices in blended and hybrid settings [10, 5].

In recent years, the focus of research has increasingly shifted toward ecosystem-based interpretations of digital learning environments, drawing on metaphors and conceptual tools from ecology [23, 43, 41]. In this perspective, a learning environment is viewed as a complex system composed of interacting components whose evolution depends on reciprocal adaptation processes. Extending the ecological notion of ecosystem to artificial systems requires the explicit identification of both the living community and the environment in which interactions occur [4]. Within this framework, Uden, Wangsa, and Damiani [41] define a digital ecosystem as a digital infrastructure designed to host networked communities and to support cooperation, knowledge sharing, and the development of open and adaptive technologies.

Building on these contributions, the DELTA Research Group (University of Turin) adopts an ecosystem-based definition of Digital Learning Environment. In this thesis, a Digital Learning Environment is defined as an ecosystem that supports teaching, learning, and competence development through the synergistic integration of a human component, a technological component, and the interactions between them [4]. This definition aligns with broader models of learning ecosystems described in the literature as complex networks of individuals, technologies, communities, and organizations whose interactions foster co-evolution and mutual adaptation [25].

The human component of the Digital Learning Environment consists of one or more learning communities, including teachers and tutors, students and their peers, and administrators responsible for managing and maintaining the digital infrastructure. The technological component includes:

- a Learning Management System, together with additional software tools and integrations designed for specific educational purposes (e.g., web-conferencing platforms, assessment systems, domain-specific applications);
- learning activities and resources, either static or interactive, accessible in synchronous or asynchronous modalities;
- technological devices through which members of the learning community access the environment, such as computers, tablets, smartphones, or interactive whiteboards;
- systems and instruments for data collection, recording, and analysis, as well as tools for monitoring learning-related activities (e.g., logs, sensors, eye-trackers, video-based observations).

Beyond these components, the Digital Learning Environment also encompasses the relationships between the human and technological dimensions. These relationships give rise to the learning processes enacted within the community and are shaped by the pedagogical approaches and methodological choices that inform the design of the environment [21].

The definition adopted by the DELTA Research Group provides the conceptual foundation for this research. While Digital Learning Environments offer the context in which learning processes unfold, they do not in themselves prescribe how learning pathways should be coherently structured. The model proposed in this thesis operates within this framework by introducing a macro-design layer that explicitly organizes learning outcomes, learning units, and their relationships, without altering the underlying definition of the Digital Learning Environment.

The author of this thesis is an active member of the DELTA Research Group, coordinated by Prof. Marina Marchisio Conte (University of Turin). The group investigates cognitive processes in technology-enhanced learning environments, with a particular focus on mathematics and science education at secondary and university levels. Its research activities include the design and evaluation of digital methodologies for teaching and learning mathematics, the integration of virtual learning environments with advanced computational systems and automatic assessment tools, and the development of virtual learning communities. Key research themes of the group include problem posing and problem solving with ICT, adaptive learning pathway generation, formative and summative automatic assessment, tutoring in mathematics education, teacher professional development in STEM, data-driven analysis of learning processes, and the role of digital environments in supporting quality, inclusion, and internationalization in education.

3.2 Personalized Learning

3.2.1 Theoretical Foundations of Personalization

The 2017 Horizon Report identifies the personalized learning as one of the greatest challenges for the twenty-first century [19]. With "personalized learning" we mean the strategies put in place to support students' learning, which must be effective from a pedagogical point of view and based on their needs in the short, medium and long term. These strategies can have several main objectives, such as:

- help students understand their own needs or aspirations;
- fill gaps in learning outcomes;
- increase student engagement;
- make students independent in choosing their learning path.

Another definition of personalized learning was given by Beese: ”Educational personalization is best conceived, in a broad sense, as what occurs in any process that uses information from or about a student to generate plans or educational decisions for that student ” [7]. One theory that describes the design characteristics of personalized learning is that of Walkington and Bernacki [44]. This theory focuses on the ways in which a learning environment can be modified for the benefit of students' cognitive, motivational and affective processes that influence their learning. In this theory, three dimensions relevant to learning theories are identified, based on which personalized learning strategies can vary. The first dimension is the “variable degrees of depth”, which measures how much the daily life experiences of students affect the design of teaching activities. For example, personalization can be done by using the student's name (surface level) or by incorporating their interests (deeper level) into the content to be learned. The second dimension, called “different grain sizes”, is the granulometry of the personalization intervention, which can be at the level of the individual student, of small groups (with one or more common characteristics) or of larger groups based on more general parameters. The third dimension is finally “ownership”, that is the degree in which students are given control and choice of learning situations [44]. In this case, the personalized learning systems can be more or less automated, and therefore vary from cases in which the student has no control and automatic adaptivity is guided by a technological system, to cases in which the student can even select the content to learn. Although personalization has often been operationalized through references to learning styles or modality preferences, contemporary research increasingly emphasizes structural dimensions of personalization, such as prior knowledge, prerequisite relationships, and the organization of learning trajectories. Personalization in digital learning draws conceptually from a diverse constellation of educational theories, each offering distinct perspectives on how individual differences in learners should be accommodated when designing instructional environments.

Progressivist views emphasise the learner's autonomy and experiential engagement, encouraging systems to provide pathways that are not merely preset but responsive to personal progression. This philosophical orientation suggests that adaptive platforms should promote agency by incorporating options for self-direction within structured guidance. Behaviourist theory, although traditionally critiqued for its narrow focus on observable behaviours and neglect of cognitive processes, continues to inform feedback-driven personalization models which rely on reinforcement cycles to shape desired learning actions. When interpreted critically, this influence can be retained selectively, for example, in formative assessment loops, without constraining learners inside rigid drill-and-practice sequences.

Constructivism aligns strongly with personalization goals because it maintains that knowledge is actively constructed by the learner instead of passively received [49]. Digital environments inspired by this stance design adaptive tasks so learners confront problems requiring synthesis and contextual application, enabling meaningful interaction between prior knowledge and new content.

Cognitivist approaches intersect here by insisting that adaptive systems must accommodate cognitive structures such as working memory capacity and schema development. Applying cognitive load theory within personalization entails careful modulation of task complexity to match current proficiency levels while introducing sufficient challenge to promote growth. Platforms embedding differentiated instruction principles operationalize this balance by automatically adjusting material difficulty based on ongoing data about learners' cognitive states. Social and sociocultural theories extend personalization into collaborative dimensions. The notion of the Zone of Proximal Development (ZPD) articulated by Vygotsky informs algorithms capable of sequencing resources or peer interactions just beyond a learner's independent capability range, thereby leveraging social input to accelerate mastery [36]. In practice, recommender systems primarily personalize individual learning trajectories; however, similar analytics could be extended to support the dynamic orchestration of collaborative tasks based on complementary skill profiles.

Connectivism augments this social perspective for digital contexts by recognising that learning occurs across networked connections, both human and informational, requiring personalization strategies that integrate external nodes selectively into the learner's pathway without overwhelming relevance filters. Humanistic learning theory adds another dimension often overlooked in algorithmic models: recognition of emotional states alongside cognitive achievements [20]. Personalization rooted in humanistic principles values self-expression and intrinsic motivation, prompting systems to permit choice among thematic contexts or resource modalities aligning with affective resonance. This approach finds practical form in adaptive engines that factor user-stated interests into content selection, thereby deepening engagement through personal relevance. Technologically enabled personalization operationalizes these theories through machine learning models embedded within course infrastructures. Adaptive engines leveraging supervised classification can map behaviour patterns onto theoretical constructs, for instance, identifying when observed disengagement aligns with an unmet need for intrinsic motivation suggested by Self-Determination Theory (SDT), and initiate relevant interventions like offering more autonomy in task choice. The capacity of reinforcement learning models to optimise long-term rewards is consistent with constructivist principles in the sequencing of problem-solving challenges. This enables the development of competency over extended periods, as opposed to the pursuit of short-term accuracy [36]. Sequencing logic grounded in these frameworks maintains pedagogical coherence whilst dynamically responding to emergent learner profiles. Analytics play a critical role in bridging theory with operational personalization. By quantifying engagement levels, response accuracy patterns, collaboration metrics, and self-reported satisfaction indices, platforms can identify which theoretical lens best interprets a learner's evolving conditions [2].

For instance, high collaborative engagement paired with moderate independent performance could signal suitability for sociocultural scaffolding interventions over isolated cognitive drills. Integrating multimodal inputs, including textual contributions from forums, clickstream data from interactive modules, and assessment artefacts, supports granular decision-making consistent with educational paradigms underpinning personalization strategies. The educational literature also cautions against overfitting theoretical application solely to detected behaviours due to context distortions; environmental constraints such as device type or connectivity quality can influence observed learning styles without reflecting actual cognitive preference [3]. This underscores the need for interpretive flexibility where algorithms adapt recommendations not only based on raw interaction data but also contextual metadata describing the conditions under which those interactions occurred.

Combining multiple theoretical foundations into hybrid personalization architectures appears particularly effective when aiming for both performance gains and holistic development. A composite model might begin with behaviourist-influenced reinforcement during initial skill acquisition phases; transition toward cognitivist-informed scaffolding as schema complexity increases; embed constructivist project-based activities once foundational competence stabilises; and maintain sociocultural collaboration layers throughout [49]. Systems designed under such synthesis respect the varied trajectories learners take toward expertise while aligning adaptive responses closely with documented pedagogical rationales. Practical deployment also depends on educator involvement in tuning theoretical integration according to observed outcomes, a theme paralleling earlier analyses linking human oversight with algorithmic adaptivity. Teachers interpreting dashboards populated with analytic indicators can adjust weighting among competing theoretical priorities depending on group performance dynamics or individual anomalies [8]. This multi-level adaptability ensures that automated recommendations remain anchored within professional judgement informed by situational awareness, thus avoiding the pitfall of drifting purely on statistical inference. Reflection elements embedded into personalized pathways further consolidate theoretical coherence. By prompting learners to articulate reasoning behind chosen solutions or relate new knowledge to prior experiences, systems activate metacognitive processes central to both constructivist and cognitivist perspectives. Peer commentary opportunities infused within recommendation flows extend this reflective space outward into collaborative exchanges emblematic of sociocultural engagement principles [20].

In high-scaling environments such as massive open online courses (MOOCs), generative AI offers additional potential for embedding theoretical variety within adaptive content streams [37]. Here algorithmic differentiation may produce parallel versions of lessons emphasising analytical decomposition suitable for cognitivists; exploratory simulations resonant with constructivists; or discussion prompts facilitating social negotiation characteristic of sociocultural frameworks, all mapped dynamically against evolving learner profiles gathered through real-time activity monitoring. Ultimately personalised learning strategies anchored in clear theoretical foundations provide resilience against superficial adaptivity. Aligning machine-driven pathway adjustments with established educational principles, from progressivism's emphasis on autonomous exploration to SDT's focus on intrinsic motivation, not only strengthens pedagogical integrity but also safeguards against threadbare customization limited to surface-level metrics. Such alignment is especially pertinent where cross-platform interoperability allows credentials or mastery records generated under one system's theoretical framing to inform progression decisions elsewhere without losing interpretive fidelity [2].

3.2.2 Personalization Strategies and Technologies

Personalization strategies in digital learning environments emerge from the convergence of pedagogical models centered on learner agency and technological infrastructures capable of processing and responding to large volumes of learner data. By integrating real-time and longitudinal data streams, such as diagnostic assessments, interaction traces, learning analytics indicators, and self-reported preferences, adaptive systems can dynamically construct learning pathways that differ in pace, sequencing, modality, and contextual framing [17]. This approach represents a shift from static course structures toward responsive learning ecosystems in which personalization is an operational property instead of an ancillary feature.

A foundational strategy is competency-driven sequencing, where instructional progression is continuously adjusted according to inferred mastery levels [30]. Instead of enforcing uniform trajectories, adaptive systems reorder or revisit learning units based on formative evidence, allowing learners to consolidate prerequisite knowledge before advancing or to accelerate when mastery is demonstrated [40]. Such mechanisms have proven particularly effective in structured domains, including STEM disciplines, where conceptual dependencies can be explicitly modelled and algorithmically enforced [33]. However, contemporary implementations increasingly extend beyond STEM by aligning personalization with domain-specific learning outcomes in less structured fields, for example by tailoring argumentation tasks or multimodal compositions in language education.

Educational recommender systems constitute a central technological pillar of personalization. Drawing on collaborative filtering, content-based filtering, and hybrid models, these systems support learners in navigating extensive repositories of digital resources by aligning recommendations with prior knowledge, engagement patterns, and learning objectives [49]. Reinforcement learning approaches, such as Q-learning and deep Q-networks, further enhance adaptivity by framing personalization as a sequential decision-making problem, where recommendations aim to optimize long-term learning gains beyond short-term engagement metrics [36]. From this perspective, the recommendation process becomes an ongoing pedagogical intervention rather than a one-time act of content selection.

Learning analytics amplify these strategies by transforming raw interaction data into interpretable signals that inform adaptive decisions [48]. Patterns in time-on-task, resource navigation, and assessment performance allow systems to infer learner readiness, preferred modes of engagement, and potential disengagement risks. These insights support style-sensitive restructuring of learning activities: sequential learners may benefit from stepwise problem decomposition, while holistic learners may receive conceptual overviews before engaging with detailed tasks [30]. Importantly, personalization extends beyond cognitive dimensions to include social interaction preferences. Collaborative learners may be directed toward peer-based activities and shared problem-solving environments, whereas more autonomous learners can follow self-paced pathways enriched by optional social interaction [34].

Generative artificial intelligence introduces a further layer of personalization by enabling scalable content diversification [37]. Adaptive systems can generate alternative explanations, representations, or practice tasks aligned with learner readiness and modality preferences beyond the selection of resources from a fixed pool. Visual-spatial learners may receive diagrammatic explanations, while verbal-linguistic learners are supported through narrative elaborations, without imposing additional content production burdens on instructors. Analytics-driven feedback loops then allow systems to evaluate the effectiveness of these variants, refining personalization strategies over time.

While these technologies are effective in personalizing access to content and sequencing learning activities, they often operate primarily at the level of resource selection and not at the level of learning path structure.

Personalization strategies increasingly intersect with microcredentials ecosystems. When embedded within adaptive platforms, microcredentials do not merely certify learning outcomes but actively inform subsequent recommendations through metadata describing task context, skill focus, and performance conditions [2]. In this way, credentialing artifacts become functional elements within the personalization loop, enabling continuity across courses and supporting the construction of individualized, competency-based learning pathways that extend beyond isolated instructional units (as we can see later in the next section 3.3).

Despite the increasing centrality of automated mechanisms, effective personalization remains inherently hybrid. Educator oversight plays a crucial role in interpreting algorithmic outputs, validating adaptive decisions, and ensuring alignment with pedagogical intentions and contextual constraints [18]. Personalized learning in digital environments thus emerges from the interplay between adaptive technologies, explicit instructional design frameworks, and informed pedagogical judgment, not from algorithmic automation alone.

3.2.3 Challenges and Limitations

Despite the growing sophistication of personalization technologies, their pedagogical effectiveness in digital learning environments is constrained by a range of interrelated challenges. Many of these limitations stem not from technical immaturity alone, but from tensions between algorithmic optimization and foundational educational principles.

A primary pedagogical challenge concerns the risk of overspecialization. Personalization systems that rely heavily on prior behaviors, preferences, or inferred learning styles may inadvertently narrow learners' exposure to unfamiliar topics, alternative representations, or challenging cognitive demands [8]. While precise alignment between learner profiles and instructional resources can reduce cognitive overload and enhance relevance, excessive optimization risks undermining exploratory learning, interdisciplinary thinking, and the development of transferable competencies. From a pedagogical standpoint, effective learning often requires productive struggle and exposure to perspectives beyond immediate comfort zones, which overly deterministic personalization may suppress.

Another significant limitation relates to the complexity of modeling learning processes. Unlike consumer recommender systems, educational contexts require accounting for cumulative knowledge development, prerequisite dependencies, and evolving learner states [36]. Recommendations that disregard curricular structure may fragment learning trajectories or introduce advanced content prematurely, thereby increasing cognitive load at the expense of learner mastery. Furthermore, learner profiles inferred solely from behavioral data may conflate intrinsic preferences with contextual constraints, such as limited device access or time pressure [3]. This raises concerns about the validity of analytics-driven personalization unless behavioral indicators are triangulated with self-report instruments and pedagogical interpretation [48].

Teacher readiness constitutes a further pedagogical constraint. Even when advanced personalization tools are available, their effective use depends on instructors' understanding of both the underlying pedagogical models and the operational logic of adaptive systems [38]. Insufficient professional development can result in superficial adoption, where personalization features are activated but not meaningfully integrated into instructional decision-making [37]. This disconnect may weaken alignment between adaptive sequencing, learning outcomes, and assessment practices, particularly in large-scale online courses.

Ethical and equity-related issues intersect closely with pedagogical limitations. Algorithmic bias embedded in training data can perpetuate existing educational inequalities by systematically steering certain learner groups toward less demanding pathways or lower-quality resources [24]. From a pedagogical perspective, such dynamics conflict with principles of inclusivity and equal opportunity for intellectual growth. Transparency and explainability therefore become essential not only for ethical compliance but also for pedagogical legitimacy: learners and educators must understand why specific recommendations are generated in order to trust, contest, or override them when necessary [24].

Accessibility constraints further limit the reach and equity of personalized learning. Many adaptive systems presuppose stable connectivity and continuous data exchange, conditions not universally met across institutions or regions [19]. It is important to note that offline or low-bandwidth adaptations may, in principle, preserve access. However, such adaptations frequently result in a reduction in the immediacy and granularity of personalisation. This has the potential to reinforce disparities in learning support, instead of mitigating them.

The integration of microcredentials into personalized pathways introduces additional pedagogical risks. When credential schemas are poorly aligned with broader competence frameworks, learning trajectories may become fragmented into isolated skill units lacking coherent developmental logic [16]. Such fragmentation complicates both formative guidance for learners and summative interpretation by external stakeholders, including employers and accreditation bodies.

Collectively, these challenges underscore that personalization is not intrinsically beneficial. Its educational value depends on deliberate pedagogical design choices, transparent and ethically grounded algorithmic practices, sustained investment in educator capacity building, and an ongoing effort to balance efficiency with intellectual breadth, learner autonomy, and meaningful competence development. Taken together, these limitations highlight the need for design-oriented models capable of governing personalization at the structural level, ensuring coherence, transparency, and equivalence across learning paths.

3.3 Microcredentials

3.3.1 What are Microcredentials

Microcredentials are increasingly recognised as a flexible form of certification designed to attest the achievement of specific learning outcomes following a small volume of learning. Unlike traditional qualifications, which are typically associated with extended and formally structured programmes, microcredentials certify targeted and clearly delimited learning achievements that can be acquired across formal, non-formal, and informal learning contexts.

According to the European approach to microcredentials[1], a microcredential represents the record of assessed learning outcomes that a learner has obtained through a short, focused learning experience. These learning outcomes are evaluated against transparent and predefined standards and are explicitly linked to identifiable knowledge, skills, and competences responding to societal, personal, cultural, or labour market needs. Importantly, microcredentials are conceived as complementary to traditional degrees and qualifications without serving as substitutes, supporting lifelong and life-wide learning trajectories.

A distinguishing feature of microcredentials pertains to their orientation towards learning outcomes as opposed to learning duration. The workload associated with a microcredentials is therefore expressed through notional learning effort, commonly aligned with the European Credit Transfer and Accumulation System (ECTS) where applicable, while maintain-

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[1] The content of this section is based on official European policy documents and reference materials on microcredentials, made available by the European Commission and accessible at: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021DC0770`.

ing flexibility for providers operating outside higher education frameworks. This outcome-oriented perspective facilitates comparability and transparency across providers and sectors.

Microcredentials are learner-owned, portable, and shareable. They can be stored in secure digital formats and communicated across institutional and national boundaries, supporting mobility and recognition. Their design typically includes a standardised set of descriptive elements, such as the identity of the learner and issuer, learning outcomes, workload, level, assessment method, and quality assurance mechanisms, ensuring clarity and trust for all stakeholders involved.

From an educational perspective, microcredentials enable modularisation of learning opportunities and support flexible learning pathways. They may be issued as standalone credentials or combined with other microcredentials to form larger, coherent learning trajectories. This modular structure aligns with contemporary demands for upskilling and reskilling, allowing learners to progressively build and document competences in response to evolving educational and professional contexts.

Overall, microcredentials can be understood as a structured and quality-assured mechanism for recognising granular learning achievements, positioned at the intersection of lifelong learning, employability, and educational innovation.

3.3.2 Microcredentials and Flexible Learning Paths

Microcredential frameworks are frequently presented as enablers of flexible learning paths, since they support modular skill acquisition without requiring full-degree commitments [2]. Their granularity allows learners to select, combine, and reconfigure learning experiences over time, adapting progression to personal goals, professional needs, or emerging opportunities, rather than following rigid and linear programme structures [19]. In this sense, microcredentials can function as discrete, verifiable markers of competence embedded within broader qualification ecosystems, contributing to more responsive and competence-oriented learning architectures [2].

A defining mechanism behind flexibility is *stackability*: credentials earned for distinct competencies can accumulate towards higher-level certifications, enabling progression without redundancy in instruction or assessment [16]. This structure aligns with competency-based perspectives where advancement is linked to demonstrated mastery without being constrained by fixed duration [19]. However, to preserve coherence, stackability requires explicit institutional rules for validation and integration, otherwise the pathway risks becoming a collection of fragmented achievements with limited interpretability [16].

Within digital learning environments, the connection between microcredentials and flexible paths becomes tighter when credentials are integrated into personalization processes. When a learner earns a microcredentials, the credential can be treated not only as a record of achievement, but also as an actionable data artifact within the learner model, unlocking or recommending subsequent learning opportunities that are consistent with what has been achieved [2]. In such configurations, adaptive engines can map credential metadata to next-step recommendations, sequencing additional modules, reinforcement activities, or advanced challenges based on performance trends and pacing patterns detected through learning analytics [22]. This transformation of micro-credentials into active components of a personalised pathway is a significant development in the field, moving beyond a static, transcript-like marker to a dynamic, flexible and adaptable system.

From this perspective, microcredentials can support personalization at two complementary levels. First, they structure *what* a learner may pursue next, by making progression options explicit and modular (e.g., alternative routes towards comparable higher-level outcomes) [19]. Second, they can influence *how* the learner progresses, since analytics-informed systems may recommend different resources, modalities, or learning units for the same credential goal, balancing acceleration in strong areas with reinforcement where gaps are detected [22]. Generative AI may further expand this personalization by producing differentiated preparatory resources aligned with learner readiness tiers, while preserving common assessment criteria for credential issuance [37]. Overall, microcredentials can therefore be understood as modular building blocks that make flexible learning paths operational and, when embedded in analytics-driven environments, support more coherent forms of personalized progression [2, 19].

3.3.3 Microcredentials in UNITA

UNITA – *Universitas Montium* is a European University Alliance coordinated by the University of Turin, bringing together higher education institutions located in rural and mountainous regions across Europe, including universities from Italy, France, Spain, Portugal, Romania, and Switzerland, all sharing a common commitment to regional development, multilingualism, and inclusive higher education [15]. The alliance aims to promote inclusive, student-centred, and flexible learning models, with a strong emphasis on multilingualism, sustainability, digital transformation, and European citizenship. Within this framework, UNITA actively supports innovative educational formats that enhance mobility, lifelong learning, and skills recognition across institutional and national boundaries.

Microcredentials play a strategic role within UNITA's educational vision. In line with European recommendations, UNITA microcredentials are conceived as short, targeted learning units designed to certify specific learning outcomes and competences, and to support flexible and personalised learning pathways. They can be integrated into existing degree programmes or offered as standalone learning opportunities, addressing both traditional students and lifelong learners. The alliance has defined common specifications to ensure coherence, quality assurance, accessibility, and interoperability of microcredentials across partner universities.

The pedagogical and organisational framework developed within UNITA specifies standard elements for microcredentials, including learning outcomes, workload, assessment methods, digital delivery, and the awarding of digital badges. Particular attention is given to inclusivity, student-centred design, and alignment with the thematic priorities of the alliance, such as intercomprehension among Romance languages, renewable energies, circular economy, cultural heritage, digital transition, global health, inclusive societies and European citizenship. These specifications provide a shared reference model while allowing institutional flexibility in implementation.

The author of this thesis is directly involved, together with two of the thesis supervisors, in the UNITA task group dedicated to microcredentials. This task is currently engaged in defining new UNITA microcredentials and in reflecting on pedagogical models capable of ensuring coherence, quality, and scalability across the alliance. Within this context, the adoption of the SPIRAL model has been proposed as a reference framework for the design of UNITA microcredentials. The model aims to support structured alignment between learning outcomes, learning activities, assessment, and personalisation mechanisms within digital learning environments. The SPIRAL model and its role in the design of UNITA microcredentials will be presented and discussed in detail in a later chapter of this thesis.

3.3.4 Global Adoption of Microcredentials

The global adoption of microcredentials is characterised by significant variability across regions, reflecting differences in policy frameworks, institutional readiness, technological infrastructure, and cultural attitudes towards modular forms of certification. In some higher education systems, microcredentials have been integrated into formal qualification pathways, while in others they remain complementary instruments, primarily supporting continuing education and workforce development instead of replacing traditional degrees [19].

Contexts with advanced digital infrastructures have generally enabled deeper integration of microcredentials within learning management ecosystems, supported by interoperable platforms, open badge standards, and analytics-enabled recognition processes [2]. In these environments, credential portability facilitates both academic progression and employability, particularly in sectors where discrete and rapidly evolving skill sets align closely with labour market demands. Conversely, in regions with limited connectivity or institutional capacity, adoption is constrained by infrastructural and organisational barriers, prompting the development of hybrid delivery models and localised adaptations aimed at preserving accessibility and inclusion [17].

Policy alignment plays a decisive role in shaping adoption trajectories. In Europe, initiatives connected to the Bologna Process promote harmonisation and cross-border recognition, enabling learners to accumulate modular credentials without loss of recognition value [19]. In contrast, in North America and Australasia, microcredentials often emerge through institution–industry partnerships or community-based initiatives, expanding recognised learning outcomes beyond strictly academic competencies and reinforcing alternative pathways into higher education and employment [16].

Despite their potential, microcredentials raise concerns related to fragmentation of qualification landscapes and the interpretability of increasingly complex credential portfolios [16]. Addressing these issues requires situating microcredentials within coherent competency frameworks that clarify progression, aggregation, and long-term value. Overall, global adoption reflects the interplay between technological capacity, regulatory support, and pedagogical coherence, with the most sustainable implementations emerging where these dimensions are aligned [2, 19].

3.4 Instructional Design

3.4.1 Instructional Design Models for DLEs

Instructional design models in digital learning environments (DLEs) encompass structured approaches that guide how learning materials, activities, and assessments are conceived, organized, and delivered in technologically mediated contexts. These models aim to align pedagogical goals with the interactive and data-driven possibilities offered by modern platforms while accommodating diverse learner profiles and preferences.

Designing for DLEs involves not only sequencing instructional content but also integrating adaptive mechanisms, social interaction channels, and continuous monitoring tools that can respond dynamically to learner performance patterns. One influential perspective, rooted in the principle of constructive alignment, emphasizes mapping teaching objectives to all components of the system prior to implementation [9]. This mapping underpins decisions about interactive content creation, tool selection, instructional strategies, and assessment criteria. For instance, defining cognitive skill targets early allows instructional designers to choose media formats, text, video, simulation, aligned with these skills while ensuring content delivery mechanisms support flexibility in learning modalities. Within DLEs such mappings are often operationalized through instructional matrices that align competencies with specific resource types or interaction forms. This prevents fragmentation by maintaining coherence across dispersed learning elements.

Procedural components in e-learning designs frequently include content delivery systems capable of integrating diverse media types; monitoring and management subsystems correlating learning objects with expected outcomes; communication modules supporting peer and teacher interactions; and collaboration spaces for joint problem-solving [28]. Incorporating these components into a unified model means balancing synchronous tools like web conferencing with asynchronous affordances such as discussion boards or interactive wikis. The interplay among them shapes the pedagogical texture of the environment, high multimedia integration supports engagement but requires scaffolding to manage cognitive load, while strong collaboration functions bolster social constructivist dimensions at the risk of uneven participation if moderation is weak.

Analyses within contemporary instructional design research suggest an increasing focus on aligning design structures with Continuous Learning Environments (CLEs). In CLE-oriented models, technological capabilities like hyperlinking are employed to organize and connect content segments logically according to instructional analysis of goals [1]. Sequencing here becomes important: deciding which module proceeds another based on identified prerequisite knowledge safeguards coherent progression. Designers frequently work alongside subject-matter experts in determining Web link relevance, filtering available online resources for alignment not just with topic scope but also desired cognitive engagement levels.

From a theoretical lens, behaviourist, cognitivist, and constructivist paradigms still inform instructional model choices in DLEs [42]. Behaviourist-aligned designs use pre-structured tasks broken down systematically; cognitivist versions leverage task analyses to form scaffolded learning activities using varied strategies; constructivist approaches integrate real-world materials allowing multiple perspectives in problem solving. A blended model may segment a course into phases, initially structured for foundational skills acquisition using behaviourist repetition, followed by scaffolded consolidation under a cognitivist frame, culminating with open-ended projects encouraging constructivist exploration.

Personalization capabilities embedded in DLEs add complexity to instructional design. Models incorporating analytics allow designers to modify both sequence and presentation format based on data-driven insights into learner proficiency [30]. For example, fuzzy cognitive diagnostic frameworks quantify mastery along a continuum rather than binary pass/fail states, enabling more granular adjustments during instruction planning. In adaptive designs informed by such diagnostics, resources may be introduced earlier or later depending on recorded mastery scores between 0 and 1, a feature absent from traditional fixed-sequence pedagogy. The role of student-centred frameworks manifests strongly where personalization intersects with designed flexibility. Learner-centred configurations reposition instructors from primary information sources toward facilitators guiding exploratory pathways [45]. Instructional models here embed decision points where learners choose task formats or thematic contexts according to interest signals captured within the LMS. To sustain coherence amid flexibility, scaffolds like rubrics ensure different task options map consistently onto competency frameworks. Design strategies are also sensitive to blended learning arrangements wherein online segments complement face-to-face components [26]. In such designs, content delivery strategies must account for varying student maturity levels and study contexts. Undergraduate professional courses might prioritise hands-on activities during physical sessions supported by online preparatory modules; fully online equivalents could replicate these experiences via simulation tools coupled with peer discussion forums managed asynchronously.

Systematic instructional design for award-winning online courses illustrates a sequential approach starting from course descriptions and objectives before advancing toward activity generation [32]. This front-loading of objective articulation ensures later development stages remain consistent with intended outcomes, important when integrating complex technologies like adaptive recommenders or generative AI-driven resource creation. The systematic method supports evaluation phases too: well-documented objectives enable alignment checks between planned outcomes and measured achievements during formative or summative assessment cycles.

A forward-looking element involves embedding resilience into instructional design so environments can shift modality without loss of coherence under disruptive events [1]. Models incorporating both synchronous live interaction opportunities and asynchronous self-study modules allow rapid reconfiguration from hybrid formats into fully remote modes should circumstances require it. Interoperability across platforms becomes critical here: integrated architectures permit seamless migration between physical classroom device setups, home-based access points, and mobile delivery channels while preserving data continuity critical for analytics-informed adaptivity.

Finally, evolving models recognise the influence of institutional strategic alignment on design choices. Instructional plans are shaped not purely by pedagogical concerns but by broader agendas like inclusivity compliance standards or long-term workforce development goals tied to industry partnerships [28]. Embedding accessibility guidelines within initial model phases ensures all media formats meet cross-device compatibility standards; linking curricular sequences directly with microcredentials pathways strengthens relevance for external stakeholders as discussed previously in Section 3.3.3.

In sum, instructional design models for DLEs combine structured procedural elements with adaptivity layers informed by analytics and cognitive frameworks. They operate at intersections connecting theory-driven pedagogy with multi-modal technological infrastructure while sustaining responsiveness across varied learner cohorts. Designing within this multi-constraint space demands artefacts, objectives maps, competency-resource matrices, sequencing protocols, that maintain coherence amid ongoing personalization pressures and environmental volatility [1, 28, 42]. Within instructional design models for digital learning environments, learning outcomes and learning objects play a central role in translating pedagogical intentions into concrete design artefacts. The following section examines these two elements, which underpin the structuring, sequencing, and personalization of learning pathways.

3.4.2 Learning Object and Learning Outcomes

Learning Outcomes

The "2017 European Quality Framework" [2] defines learning outcomes as "[. . .]statements of what an individual should know, understand and/or be able to do at the end of a learning process, which are defined in terms of knowledge, skills and responsibility and autonomy". The learning outcomes perspective is used for a number of different purposes, the most important being:

- ▷ Qualifications frameworks and their level descriptors

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[2] Council recommendation on the European Qualifications Framework for lifelong learning and repealing the recommendation of the European Parliament and of the Council of 23 April 2008 on the establishment of the European Qualifications Framework for lifelong learning, 22 May 2017 (2017/C 189/03), Official Journal of the European Union

- ▷ Qualification standards
- ▷ Curriculum development
- ▷ Assessment and validation
- ▷ Quality assurance
- ▷ Teaching and training

For all these purposes the learning outcomes approach strengthens the focus on the individual learner and the level of knowledge, skills and competence she/he is expected to achieve.

Learning Objects

The concept of learning objects has several definitions in the literature. The term *Learning Object* (in this thesis, the term *Learning Object* is abbreviated as *LOb*) is often used interchangeably with *learning material*, *learning resource* or *educational resource*.

The Learning Technology Standards Committee use the term learning object to describe small instructional components [46]. The complete definition is the following:

> Learning Objects are defined here as any entity, digital or non-digital, which can be used, re-used or referenced during technology-supported learning. Examples of technology-supported learning include computer-based training systems, interactive learning environments, intelligent computer-aided instruction systems, distance learning systems, and collaborative learning environments. Examples of Learning Objects include multimedia content, instructional content, learning objectives, instructional software and software tools, and persons, organizations, or events referenced during technology supported learning. ([13])

Based on this definition, more authors produce other definitions of Learning Object; David Wiley defines a Learning Object as *any digital resources that can be reused to support learning* ([46]). The first difference that we could notice from these two definition is that the second one implies that all learning objects are digital. In this research, we are aligned with Wiley definition. Based on this definition, Wiley also produced a taxonomy of learning object types and a list of characteristics that distinguish them. The purpose of the taxonomy is to differentiate possible types of learning objects available for use in instructional design [46]. In the same work, Wiley goes beyond the traditional representation of Learning Object through the metaphor of LEGOs (or other children's toys). This metaphor is used for the purpose of making clear what the goal of using LOb is: that is, to create small pieces of instruction (LegosTM) that can be assembled (stacked together) into some larger instructional structure (castle) and reused in other instructional structures (e.g., a spaceship) [46]. As the author points out, however, the use of this metaphor implicitly leads to the conclusion that all properties valid for LEGOs are also valid for LOb. But this conclusion is obviously false. An easy counterexample is the case of combination: taken two Lego bricks, it is always possible to combine them, but this is not always true in the case of LOb. Another descriptive metaphor proposed by the author, and which we have partially endowed in this research, is the metaphor of the atom. An atom is a small *thing* that can be combined and recombined with other atoms to form larger *things* ([46]). The metaphor of atoms is often used to describe Learning Objects due to their properties. However, Wiley's definition and metaphor do not address two important aspects: granularity and combination (as outlined by Bruschi and Perissinotto in their work([11])). The discussion around granularity revolves around the minimum size a learning object should have. Wiley notes that the atom metaphor also encompasses this point. When considering atoms, we must also acknowledge the existence of subatomic particles with varying properties that combine to form different atoms. Therefore, it is necessary to establish a minimum measure for defining a Learning Object. Another unresolved issue pertains to the combination of LObs, as it is not clear from the current definitions how this can be achieved. In his work, Wiley proposes a taxonomy of Learning Object types, without giving an explicit answer on how they can be combined. The taxonomy is presented below:

- ▷ Fundamental: An individual digital resource uncombined with any other, the fundamental learning object is generally a visual (or other) aid that serves an exhibit or example function.

- ▷ Combined-closed: A small number of digital resources combined at design time by the learning object's creator, whose constituent learning objects are not individually accessible for reuse (recoverable) from the combined-closed learning object itself.

- ▷ Combined-open: A larger number of digital resources combined by a computer in real-time when a request for the object is made, whose constituent learning objects are directly accessible for reuse (recoverable) from the combined-open object.

- ▷ Generative-presentation: Logic and structure for combining or generating and combining lower-level learning objects (fundamental and combined-closed types). Generative-presentation learning objects can either draw on network accessible objects and combine them, or generate objects and combine them to create presentations for use in reference, instruction, practice, and testing.

- ▷ Generative-instructional - Logic and structure for combining learning objects (fundamental, combined - closed types, and generative - presentation) and evaluating student interactions with those combinations, created to support the instantiation of abstract instructional strategies.

In a 2007 paper, Chiappe Laverde and colleagues [12] started from Wiley's definition and proposed another one in a more articulated form:

> A Learning Object (LO) is a digital, self-contained, reusable entity with a clear learning aim that contains at least three internal changing components: content, instructional activities, and context elements. As a complement,the learning object should have an external component of information which helps its identification, storage, and recovery: the metadata. ([12])

Building on these definitions, this research adopts Wiley's conceptualization of Learning Objects as reusable digital resources and extends it by addressing unresolved issues related to granularity, composability, and pedagogical autonomy. In particular, the proposed model introduces the Learning Unit as a distinct object of micro-design, conceived as an autonomous and pedagogically meaningful aggregation of learning objects, closely aligned with the notion of Autonomous Learning Objects discussed by Bruschi and Perissinotto [11]. This extension enables a clearer separation between reusable digital learning resources and the instructional structures required to ensure coherence, adaptability, and meaningful learning pathways.

This state of the art shows that, despite significant advances in digital learning environments, personalization strategies, and adaptive technologies, the problem of designing coherent and equivalent learning paths remains largely unresolved. The need for a model that explicitly structures learning outcomes, modular learning units, and their relationships at the course level therefore motivates the introduction of the SPIRAL model in the following chapter.

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Chapter 4

The SPIRAL Model: Student-centred Personalization of Individual Education through Reusable and Autonomous Learning Units

4.1 Background

The SPIRAL model has been primarily conceived within the context of online/hybrid courses, but its principles can be extended to other learning environments as well. It is specifically designed for the creation and implementation of online microcredentials. As microcredentials are short, focused learning experiences that allow students to acquire specific skills and competencies, they are an ideal testing ground for the SPIRAL model for several reasons. Firstly, the compact nature of microcredentials facilitates rapid iteration and feedback, enabling us to refine the model quickly based on real-world data. Secondly, microcredentials often attract a diverse range of learners, providing a rich dataset to assess how well the SPIRAL model can personalize learning across different backgrounds and learning styles. Lastly, the growing popularity of microcredentials in both academic and professional contexts ensures that insights gained from this environment will be highly relevant and applicable, offering significant value to both educators and learners. However, when referring to microcredentials as small courses, from this point forward in the model description, we will use the term *course* more generically to encompass both MOOCs and microcredentials, or also to a similar e-learning context.

As discussed in the instructional design chapter, creating an online course involves several complex phases. One of the fundamental phases is the course design, which includes the definition of course objectives, identifying the target audience, outlining content, and designing learning activities. This phase is critical for the course's success as it establishes the learning path and assessment methods. Course objectives should be measurable, realistic, and unambiguous. Additionally, defining the course audience enables customization of content and learning activities to meet their needs and skills. It is also important to outline the course content clearly and logically. The course content must be organised logically and coherently to facilitate student learning.

The design phase can be divided into two levels: macro-design and micro-design, with one following the other. In the macro-design phase, course outcomes, target audience, content, and learning units are defined.

During the micro-design phase, designers create learning activities, assessment methods, and instructional materials for every designed learning unit. The model proposed here focuses on the macro-design phase. This model aims to standardise the metadata available for learning units, making it easier to search for and share instructional materials. This uniformity is crucial for applying comparative algorithms to personalise students' learning experiences. Additionally, we aim to develop an editor for designing online courses that incorporates the features and principles of the SPIRAL model, facilitating the creation of personalized and adaptive learning experiences. Despite the fact that the SPIRAL model is motivated and illustrated through specific institutional and policy-related contexts, such as modular and outcome-based educational frameworks, its design principles are not inherently bound to these settings. Instead, the focus is on more general challenges concerning the structuring, comparison, and personalisation of learning paths in modular educational environments.

4.2 The SPIRAL Model

The SPIRAL model is a design framework for courses in digital learning environments, conceived as a combined macro and micro-design model aimed at supporting the structured design of personalized learning paths in modular, outcome-oriented contexts. It is not intended as a universal instructional design theory, but as a design-oriented approach to governing personalization.

SPIRAL stands for Student-centered Personalization of Individual education through Reusable and Autonomous Learning units. The SPI part of the acronym (Student-centred Personalization of Individual education) refers to the idea that the student is at the centre of the learning process. Student-centred learning offers students the opportunity to decide at least two things: what material to learn and how to learn it. However, these decisions involve two different levels of content customisation, a more general and a more specific one. With regard to the more general one, the choice of what to learn is very much at the centre of the research landscape (see Section 3.2.2). There are many learning systems/sites and/or platforms that use recommandation systems to suggest courses for users to take according to their aptitudes, preferences and past experiences. At a more specific level, once a topic to be learned has been selected, several alternative learning paths may be available. These different paths can lead to the same learning outcome and can therefore be considered equivalent, although they follow distinct sequences. Each learning path can be understood as a sequence of learning units (a more precise definition will be provided in the next section). Within this model, we propose a structuring of these units that enables their comparison while also making their differences visible to the learner. In this way, students can choose which path to follow while maintaining control over their own learning process. The second part of the acronym (RAL - Reusable and Autonomous Learning units) is intended to emphasise the main characteristics of these learning units. As we can see later, the main idea is to connect a single Learning Unit with a Learning Outcome. In this way, the learning pathway is defined by a set of learning outcomes, but students can choose the learning units he or she wishes to use to achieve the same (or equivalent, as we will see later) learning outcomes. The R part of the acronym refers to the idea that the learning units should be reusable. This means that the learning units should be designed in a way that they can be used in different contexts. The A part of the acronym refers to the idea that the learning units should be autonomous, self-contained. This means that the learning units should be able to work independently of the context in which they are used. This means that the learning units should be designed in a way that they can be used in a modular way, as we can see in the next section dedicated to the entities of the model.

The following sections introduce the conceptual entities and relationships that form the basis of the SPIRAL model: learning outcomes and the relationships among them, learning units and learning paths.

4.2.1 Learning Outcomes

In the paragraph 3.4.2 we have introduced the definition of Learning Outcomes as a ”statements of what an individual should know, understand and/or be able to do at the end of a learning process”. In our model, the goal is to add features to the learning outcomes. In particular, for us a learning outcome is composed of:

- ▷ the statement/ the sentence that represent the Learning Outcome. This sentence will be composed of

  Verb + Object

  In this work, the verbs used in Learning Outcome statements are selected from those associated with a specific level of Bloom’s taxonomy [60]. The second component of each statement corresponds to the object of the verb. As discussed in Section 3.4.2, and following the framework proposed by Anderson and Krathwohl [60], this object represents the type of knowledge involved, which may be factual, conceptual, procedural, or metacognitive.
- ▷ Topic. Compared to the previously declared object, the topic defines a more general topic, which may be inserted from a hierarchical topic structure
- ▷ level of the Bloom’s taxonomy
- ▷ type of LO (parent or child) in the context in which the Learning Outcome is defined

Within the SPIRAL model, relationships among Learning Outcomes play a fundamental role in structuring learning pathways and enabling the construction of personalized and alternative learning trajectories. Such relationships may originate from two distinct processes: intentional instructional design and automated computational inference.

The first type consists of *design-time relationships*, which are explicitly introduced by the teacher during the macro-design phase of the course. These relationships reflect intentional pedagogical choices and constitute structural constraints of the learning pathway that cannot be violated during course execution. In particular, this category includes prerequisite relationships between Learning Outcomes, which express necessary conditions for didactic progression and are directly reflected in the organization of the associated Learning Units.

The second type consists of *infered relationships*, which are automatically generated by the system through computational analysis of the textual formulations of Learning Outcomes and the associated metadata. These relationships rely on a measure of semantic similarity and take into account the cognitive level associated with each Learning Outcome, expressed in terms of Bloom's taxonomy. Their purpose is to identify meaningful correspondences between learning objectives designed in different contexts or belonging to alternative learning pathways. Infered relationships do not replace design-time ones, but rather complement them by providing an additional informational layer that can be exploited to support personalization, recommendation processes, and the exploration of alternative learning paths. The formal definition, computation, and operational use of these relationships are discussed in detail in Sections 5.1.3 and 5.2.2, where the underlying algorithm and its integration into the graph-based representation of the SPIRAL model are presented.

With respect to design-time relationships, it is necessary to distinguish between two types of Learning Outcomes according to the level of design to which they refer. *Macro Learning Outcomes* are defined at the level of the entire course and answer the question: *What are the learners able to do when they complete the course?*. *Micro Learning Outcomes*, instead, are associated with the individual Learning Units that compose the learning path and answer the question: *What are the learners able to do when they complete this learning unit?*.

The distinction between macro and micro Learning Outcomes is motivated by the fact that macro Learning Outcomes are generally too broad to be directly assessed. They are therefore achieved through the construction of a learning pathway composed of micro Learning Outcomes. During the macro-design phase, the teacher must ensure that the learning path built from the micro Learning Outcomes effectively leads learners, once completed, to the achievement of the corresponding macro Learning Outcomes.

To make this relationship explicit, the model adopts a *parent/child* relationship between Learning Outcomes, intended as a many-to-many relationship: a macro-level Learning Outcome may be associated with multiple micro-level Learning Outcomes, and, conversely, a micro Learning Outcome may contribute to the achievement of multiple macro Learning Outcomes. A direct implication of this choice is that the parent/child classification is inherently contextual and dependent on the teacher's design decisions. It is therefore plausible that the same Learning Outcome may be considered a parent in one course and a child in another.

Each Learning Outcome associated with a Learning Unit must be formulated using a single observable and measurable verb. Using only one verb for each Learning Outcome helps to avoid ambiguities in the assessment of its achievement. When multiple verbs are used, even if they belong to the same cognitive level (e.g., *define* and *describe*), it may be unclear whether the competence has been fully acquired if the learner is able to perform only one of the intended actions. This issue becomes particularly evident when the verbs belong to different cognitive levels.

Definition. For each Learning Outcome LO, we define $\mathcal{L}(LO)$ as a function that associates a difficulty coefficient to the Learning Outcome. As a first hypothesis, this coefficient corresponds to the cognitive level of the Learning Outcome according to Bloom's taxonomy.[1]

Within the context of design-time relationships, prerequisite relationships between Learning Outcomes may be introduced both among macro Learning Outcomes and among micro Learning Outcomes. Given two Learning Outcomes LO_i and LO_j, LO_i is said to be a prerequisite of LO_j if the acquisition of LO_i is necessary for the acquisition of LO_j. As discussed in the following section, this relationship has a direct impact on the construction and organization of learning paths based on Learning Units.

4.2.2 Relationships between Learning Outcomes

Within the SPIRAL model, relationships between Learning Outcomes play a central role in defining learning paths and enabling the construction of alternative learning trajectories. Such relationships may originate from two distinct processes: intentional instructional design and automated computational inference. For this reason, the model distinguishes between relationships defined at design time (*design-time relationships*) and infered relationships (*infered relationships*).

Design-time relationships are explicitly introduced by the teacher during the macro-design phase of the course and represent strong pedagogical constraints that structure the intended progression of the learning pathway. The main relationship of this type is the prerequisite relationship between Learning Outcomes. Given two Learning Outcomes, LO_i and LO_j, LO_i is said to be a prerequisite of LO_j if the acquisition of LO_i is necessary for achieving LO_j. This relationship reflects a deliberate instructional choice and is established exclusively during the design phase.

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[1] In this phase, the function $\mathcal{L}(LO)$ can be interpreted as a simplified estimate of the difficulty of a Learning Outcome based exclusively on its cognitive level. In the discussion of the results, the possibility of extending this function by including additional dimensions, such as the disciplinary domain or the associated topic, will be considered in order to obtain a more fine-grained representation of Learning Outcome difficulty.

The prerequisite relationship between Learning Outcomes is directly reflected in the associated Learning Units: if LO_i is a prerequisite of LO_j, then the Learning Unit associated with LO_i must be completed before accessing the Learning Unit associated with LO_j (if it exist). In this way, design-time relationships between Learning Outcomes determine structural constraints on the ordering and accessibility of Learning Units within the learning path.

Within the context of a course, a Learning Outcome is defined as *free* if it is not associated with any Learning Unit of the designed learning path. Free Learning Outcomes typically represent prior knowledge or external competences that the course assumes learners already possess and that may appear as prerequisites without being directly assessed within the course itself.

Alongside design-time relationships, the SPIRAL model allows for the automatic generation of additional relationships between Learning Outcomes through computational analysis of textual descriptions and associated metadata. These relationships are based on a measure of semantic similarity between the textual formulations of Learning Outcomes and take into account the cognitive level associated with each outcome, expressed in terms of Bloom's taxonomy. Their purpose is to identify meaningful correspondences between learning objectives designed in different contexts or belonging to alternative learning paths.

Infered relationships do not introduce mandatory constraints, but rather provide additional information that can be used to support personalization, recommendation processes, and the exploration of alternative learning trajectories. Beyond their use at the course level, these relationships are also investigated as analytical tools for assessing the coherence and structural consistency of more complex educational structures, such as multi-course curricula and articulated training pathways. Depending on semantic similarity and on the cognitive level associated with the Learning Outcomes, such relationships may assume different conceptual forms. In particular, the model includes relationships of *connection*, indicating semantic proximity between Learning Outcomes characterized by different cognitive levels; relationships of *similarity*, identifying learning objectives that are semantically related and located at the same cognitive level; relationships of *equivalence*, identifying Learning Outcomes that are essentially interchangeable for the purpose of learning path construction; and relationships of *possible prerequisite*, suggesting a potential hierarchical dependency between Learning Outcomes that are semantically very close but associated with different cognitive levels.

Infered relationships therefore complement design-time relationships. While relationships defined by the teacher represent strong and non-violable pedagogical constraints, similarity-based relationships constitute weak or suggestive relations, whose primary role is to expand the space of possible learning trajectories while preserving the didactic coherence of the course. The formal definition of these relationships, the classification criteria, and their operational use within the model are discussed in detail in Chapter 5, where the adopted algorithm and its integration into the graph-based representation of the SPIRAL model are presented.

4.2.3 Learning Units

Starting from the definitions seen in 3.4.2 in relation to instructional design theory and in particular instructional design for working with learning objects, we started from the definition of Learning Object in [12] and added some features. In particular, our definition of Learning Unit has more common point with the definition of *Oggetto autonomo di apprendimento*([11]). In this work we will understand the term Learning Unit as a collection of three types of digital learning materials. When an entire LU is completed by the student, he/she acquires one and only one Learning Outcome. Related to the definition of Digital Learning Environment (Ref: § 3.1.4), we can classify the three kind of digital learning materials in:

- ▷ summative assessment
- ▷ resources
- ▷ activities

A summative assessment is mandatory for a collection of digital resources to be defined as a Learning Unit (LU). It enables the evaluation of whether the student has acquired the learning outcome associated with the LU. Accordingly, a LU is considered completed when the student achieves a sufficient score in the summative assessment. The remaining types of learning materials are distinguished based on their level of interactivity and on the possibility of including assessment components. This distinction between *resources* and *activities* follows the conceptual categorization adopted by the Moodle Learning Management System. In this framework, resources are non-interactive elements that provide content to learners and therefore do not allow for direct assessment. Activities, by contrast, require active learner engagement and make it possible to evaluate student performance through interaction. While summative assessments may technically be implemented as activities within the LMS, they are treated here as a separate typology due to their central role in defining a Learning Unit. Moreover, activities may support formative assessment, providing feedback during the learning process. All learning materials designed for formative evaluation are therefore included in the category of *activities*.

While Learning Objects refer to reusable digital resources, Learning Units are conceived as pedagogically autonomous design entities. Unlike complex or aggregated Learning Objects, a Learning Unit explicitly formalizes instructional intent, prerequisite structures, and assessment logic, making it a suitable abstraction for both instructional design and computational modelling. This formalization enables Learning Units to function as the core building blocks of structured and personalized learning paths within the SPIRAL framework. In the following sections we propose a taxonomy and a set of descriptors necessary for our purposes.

Descriptors of Learning Unit

Each Learning Unit (LU) is characterized by a set of descriptors defined during the design phase of the course. The following descriptors are associated with each Learning Unit:

- **Title** - a short title of Learning Unit
- **Description** - a short description of the Learning Unit
  (maybe we can think about a maximal length of this field)
- **Prerequisite** (0+) - prerequisites are learning outcomes that define the basic knowledge required to access the LU. We indicate the i-th prerequisite as P_i
- **Outgoing LO** (1) - we indicate as LO_{LU}
- **ECTS** - refers to the approximate amount of time required for an individual to complete the Learning Unit, determined by teacher (we indicate as $\Omega(LU)$.
- **Scale of difficulty** - the teacher can indicate here the estimated difficulty for this LU

In addition to these design-time descriptors, a second group of attributes is associated with the interaction between the individual learner and the Learning Unit. These attributes are dynamically updated during course execution and include:

- status (binary - completed/not completed)
- effective learning time (hard to calculate, maybe we can ask a estimation to student)

▷ rating (student can evaluate some aspects of LU, for instance completeness, clarity, ...)

As mentioned in the previous paragraph, the prerequisite relationship is derived from the connection relationship between LOs. In fact, if LO_i is connected with LO_j, then LU_{LO_i} is a prerequisite of LU_{LO_j}, meaning that in order to access LU_{LO_j}, it is necessary to complete LU_{LO_i} first. However, it is also possible for an LO to have additional prerequisites beyond those defined during the definition of LOs. These LOs are those that, within the context of a specific microcredentials, do not have a corresponding LU, meaning there is no LU that outputs that LO.

Definition. In the context of a course, we define as *free* an LO that is not associated with any LU.

Definition. For each Learning Unit LU we can define
$\mathcal{P}(LU) = \{P_i, i = 0..n | P_i \text{ is a prerequisites of LU}\}$

Definition. For each Learning Unit LU, we can define:
$\mathcal{L}(\mathcal{P}(LU)) = \max \mathcal{L}(P_i) \forall P_i \in \mathcal{P}(LU)$

Definition. An LU is defined as *atomic* if it has no prerequisites or if all its prerequisites are free LOs.

This definition establishes a minimum foundation, specific to the context, for the concept of Learning Path, hence it could be useful.

Observation. The set of prerequisites of a microcredential or a course is composed of all LO free at the end of the design process.

Definition. For each LU, we can define:
$\tau(LU) = \mathcal{L}(LO(LU_{id})) - \mathcal{L}(\mathcal{P}(LU))$

This value is a sort of measure of the difference between initial and final level of LU, but is also dependent on the context. If $\tau(LU) \leq 0$ usually there is a change of topic in terms of prerequisites and LO. If $\tau(LU) > 0$ the LU allows the learner a leap forward on his/her scale of competences in a given topic.

Characterization of LU in the Digital Learning Environment

The main idea of this section is to identify a possible characterisation of LU (as done by Wiley) according to their composition. The properties that can be used to distinguish LU are, for example, the number of activities and the number of resources. A LU that has no activities and resources (and therefore only has a summative evaluation to be defined as a LU) can be considered testing or diagnostic. Similarly, the interactivity of a LU can be assessed on the basis of the above parameters: if a LU has a very high number of activities compared to resources, it will be more likely to be interactive.

If the number of activities is equal to 0, then the LU is defined as theoretical/content-based. If the number of resources is equal to 0, then the LU is defined as practical/applied. If the number of activities and the number of passive resources are both different from zero, the ratio of the number of activities to the number of resources can be used as a scale to define the type of LU:

- $< k_1 \rightarrow$ notional
- $k_1 \leq x \leq k_2 \rightarrow$ balanced
- $> k_2 \rightarrow$ interactive

This classification can be used in the personalization phase, as it might be useful for adapting the pathway to the student's learning style. The values of k_1 and k_2 cannot be calculated empirically for now. For this reason, we decided to set $k_1 = 30$ and $k_2 = 60$. These values can then be re-evaluated in the future, perhaps even taking students' opinions into account.

4.2.4 Learning Paths

Within the SPIRAL model, a *Learning Path* is defined as a structured and sequenced progression of Learning Units designed to guide learners through the process of acquiring a specific Learning Outcome. A Learning Path is therefore not a simple linear sequence of activities, but a structured entity that reflects the prerequisite constraints defined during the design phase and that can be interpreted as a subgraph of the overall course representation. We denote the Learning Path associated with a Learning Outcome LO as the set of Learning Units that must be completed in order for the learner to achieve that Learning Outcome. In this sense, a Learning Path represents the minimal path, within a given design context, required to reach the specified learning objective. If a Learning Outcome is produced by an atomic Learning Unit, that is, a Learning Unit with no prerequisites or whose prerequisites consist exclusively of free Learning Outcomes, then the associated Learning Path coincides with the Learning Unit itself. If, on the other hand, a Learning Outcome is produced by a non-atomic Learning Unit, the associated Learning Path includes not only the Learning Unit that directly produces the Learning Outcome, but also all the Learning Units that must be completed in order to satisfy its prerequisites. More precisely, the Learning Path includes the final Learning Unit and, recursively, all Learning Units required to acquire the non-free Learning Outcomes appearing in its prerequisite set. This construction reflects the hierarchical structure induced by the design-time prerequisite relationships. For each Learning Path associated with a Learning Outcome LO_j, it is possible to define aggregate measures that characterize the overall progression and workload required by the path. In particular, the cumulative advancement provided by the Learning Path can be expressed as the sum of the progression values of the individual Learning Units composing the path, while the total workload can be estimated as the sum of the ECTS values associated with those Learning Units.

Definition. For each Learning Path associated with a Learning Outcome LO_j, we define the cumulative advancement provided by the Learning Path as

$$\tau(LO_j\,|_{LP}) = \sum_{LU_i \in LO_j|_{LP}} \tau(LU_i).$$

Definition. For each Learning Path associated with a Learning Outcome LO_j, we define the total ECTS of a Learning Path $\Omega(LO_j\,|_{LP})$ as

$$\Omega(LO_j\,|_{LP}) = \sum_{LU_i \in LO_j|_{LP}} \Omega(LU_i).$$

Alternative Learning Paths

This subsection introduces the conceptual rationale for alternative learning paths; their computational identification and formal encoding are addressed in Chapter 5. Alongside the Learning Paths derived from design-time constraints, the SPIRAL model supports the identification of *alternative learning paths*. These paths do not replace the learning paths defined during the design phase, but provide additional trajectories through which learners may achieve equivalent or closely related learning objectives. Alternative learning paths are identified by exploiting semantic similarity relationships between Learning Outcomes. Semantic similarity measures the degree to which two textual formulations share meaning and allows the identification of Learning Outcomes that express comparable learning objectives, even when they have been designed in different contexts. The minimum similarity threshold required to consider two Learning Outcomes as equivalent or inclusive is subject to evaluation and is formalized in the subsequent methodological sections. When two Learning Outcomes are identified as semantically related, a corresponding relationship can be established between their associated Learning Units. If the associated Learning Units have the same ECTS value, they can be considered equivalent from the perspective of learning path construction. If, instead, one Learning Unit is associated with a higher ECTS value than the other, it may be interpreted as inclusive, in the sense that it allows the learner to achieve learning objectives that subsume those of the Learning Unit with lower workload. By combining semantic similarity information at the Learning Outcome level with workload estimates at the Learning Unit level, the model enables the identification of alternative learning paths that allow learners to reach equivalent or higher educational outcomes through different trajectories. In this way, the space of possible learning paths is expanded while preserving pedagogical coherence and respecting the design-time constraints of the course.

4.2.5 From Conceptual Model to Algorithmic Operationalization

This chapter has introduced the entities and relationships that constitute the conceptual core of the SPIRAL model, distinguishing between pedagogically defined constraints and relationships inferred through computational analysis. These definitions establish the conditions under which Learning Outcomes and Learning Units can be related, compared, and combined, without yet committing to a specific representational formalism.

Building on this conceptual foundation, the next chapter focuses on the evolution of algorithmic procedures that operationalize these concepts and introduces the corresponding model representation. In particular, Chapter 5 presents the methods used to compute semantic similarity, integrate cognitive level information, and encode the resulting relationships within a structured representation that supports the analysis and comparison of alternative learning paths. An example of the application of the model to a course is presented in the chapter 6.

Chapter 5

Methodology

Building on the distinction introduced in Chapter 4 between design-time and inferred relationships among Learning Outcomes, this chapter focuses on the formal definition and implementation of computational mechanisms for inferring similarity-based relations. In particular, it addresses the problem of identifying and representing relationships among Learning Outcomes that are not explicitly defined during the instructional design phase, but instead emerge from the analysis of their semantic content and their role within the learning ecosystem. Semantic similarity among Learning Outcomes plays a central role in this process, as it provides both the theoretical and operational foundation for the construction of alternative and equivalent learning paths with respect to the same learning outcomes. By quantifying similarity, the SPIRAL model is able to identify learning objectives that are comparable in terms of meaning and cognitive intent, even when they belong to different courses or educational contexts. This enables a form of personalization that goes beyond local adaptations within a single course and instead operates at the level of the learning ecosystem structure.

The chapter is organized into two main and closely interconnected parts. The first part is devoted to the definition and implementation of algorithms for computing similarity among Learning Outcomes. This section discusses the methodological choices underlying the adopted similarity model, with particular attention to the semantic component and its computational formalization, as well as the implications of these choices in terms of reliability, interpretability, and consistency of the inferred relations.The second part of the chapter focuses on the integration of similarity-based relations within the graph-based representation of the SPIRAL model. In this perspective, the relations produced by similarity algorithms are not treated as isolated outputs, but as structural elements of the Learning Outcomes graph that interact with other types of relationships defined in the model. The graph-based representation makes it possible to analyse how similarity relations influence the topology of the learning ecosystem and to investigate their impact on the generation, analysis, and evaluation of alternative learning paths. Taken together, the two parts of the chapter define a coherent methodological workflow: similarity algorithms provide the inferred relations, while graph modelling enables their exploration, interpretation, and operational use within ecosystem-level, data-driven personalization strategies. This interplay between algorithmic computation and structural modelling constitutes a key prerequisite for the analyses developed in the subsequent chapters and for assessing the contribution of the SPIRAL model to the design of personalize learning paths.

5.1 Algorithm for Learning Outcome similarity

Throughout the research process, the algorithm for measuring *learning outcome similarity* has undergone a progressive evolution, driven by both theoretical considerations and empirical evidence emerging from the experimental phase. Its development has been guided by the objective of supporting, in an automated manner, the identification of meaningful relationships between Learning Outcomes, with the aim of making explicit and structurally representable the connections between the corresponding Learning Units.

Within the SPIRAL model, each Learning Unit is associated with a single Learning Outcome; consequently, the automatic identification of equivalence or implication relations between Learning Outcomes makes it possible to infer structured relationships also between Learning Units. Such relationships can be represented as directed edges within a graph-based structure modelling the course, reflecting the directional nature of learning processes and educational pathways, as will be discussed in Section 5.2.

The algorithm is not conceived as an autonomous decision-making tool, but rather as a mechanism supporting instructional design, aimed at making explicit relationships that, in design practice, are often left implicit or entrusted exclusively to the interpretation of the designer. From this perspective, learning outcome similarity is not understood as mere linguistic proximity, but as an indication of the extent to which the achievement of one learning outcome may imply or include the achievement of another.

Such a mechanism constitutes a fundamental prerequisite for the generation and analysis of alternative and personalised learning pathways and provides the basis for integrating learning analytics, recommendation functionalities, and adaptivity strategies within the Digital Learning Environment.

5.1.1 The First Version of the Algorithm

The first version of the algorithm for computing *learning outcomes similarity* was developed with the aim of providing a computational measure capable of integrating semantic affinity between Learning Outcomes with an assessment of their cognitive coherence; part of the results obtained with this formulation has been published in a contribution presented at the CELDA 2025 conference[1] [52]. The algorithm is conceived as a support tool for instructional design within the SPIRAL model, in which similarity between Learning Outcomes is not interpreted as a simple linguistic proximity, but rather as an indicator of the possibility that achieving one outcome implies or includes the achievement of another. From an operational perspective, the algorithm takes as input ordered pairs of Learning Outcomes (LO_i, LO_j), each expressed in textual form. Each Learning Outcome is preliminarily assigned a cognitive level according to Bloom's taxonomy through an automatic linguistic classification process, based on a transformer model fine-tuned to recognise cognitive levels from the full textual formulation of the outcome [53]. This approach makes it possible to overcome a purely lexical assignment of Bloom levels, by taking into account the overall syntactic and semantic context and ensuring a more coherent and scalable classification, which is necessary for systematically integrating the cognitive dimension within the algorithm.

The semantic representation of Learning Outcomes is obtained using a Sentence-BERT model, specifically *all-MiniLM-L6-v2*, selected for its balance between semantic accuracy and computational efficiency. Each Learning Outcome is transformed into a vector representation $\vec{e_i}$ derived from the descriptive text of the outcome; prior to computing the embeddings, Bloom-related action verbs are removed from the text, in order to prevent lexical similarities exclusively linked to the cognitive dimension from artificially influencing the semantic comparison. The base semantic similarity between two Learning Outcomes is then defined as the cosine similarity between the corresponding vectors:

$$\text{sim}_{sem}(LO_i, LO_j) = \cos(\vec{e_i}, \vec{e_j})$$

This semantic component is subsequently adjusted by an asymmetric correction factor designed to account for differences between the cognitive levels

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[1] International Conference on Cognition and Exploratory Learning in Digital Age

associated with the two Learning Outcomes. Let $\mathcal{L}(LO)$ denote the Bloom level assigned to a Learning Outcome; the asymmetric factor $T(LO_i, LO_j)$ is defined as:

$$T(LO_i, LO_j) = \begin{cases} 1, & \text{if } \mathcal{L}(LO_i) \geq \mathcal{L}(LO_j) \\ e^{-k\cdot(\mathcal{L}(LO_j)-\mathcal{L}(LO_i))}, & \text{if } \mathcal{L}(LO_i) < \mathcal{L}(LO_j) \end{cases}$$

where k is a decay parameter controlling the intensity of the penalisation applied to transitions towards higher cognitive levels. In this first formulation, the value of k was arbitrarily set to 0.5, with the aim of introducing a gradual penalisation that reflects the cognitive hierarchy without completely suppressing the contribution of semantic similarity. However, on the basis of the empirical results discussed in the subsequent sections, this formulation was later reconsidered and ultimately abandoned; for this reason, no empirical optimisation of k was carried out, as the research focus shifted towards the development of a revised version of the algorithm adopting a different integration strategy (see section 5.1.3). In this formulation, Bloom's taxonomy is treated as an ordered and uniformly spaced cognitive scale, allowing differences between levels to be operationalised through a numerical distance. This assumption represents a deliberate simplification, adopted to enable the computational integration of cognitive information within the similarity measure, and is not intended to reflect the full qualitative complexity of cognitive transitions in learning.

The final directional similarity measure is therefore defined as:

$$\text{sim}(LO_i \to LO_j) = \text{sim}_{sem}(LO_i, LO_j) \cdot T(LO_i, LO_j)$$

The resulting formulation produces an intentionally asymmetric similarity score, such that the values for (LO_i, LO_j) and (LO_j, LO_i) differ when $\mathcal{L}(LO_i) \neq \mathcal{L}(LO_j)$, reflecting the inherently directional nature of learning processes.

Figure 5.1 provides a graphical overview of the methodological workflow adopted in the first version of the similarity algorithm, discussed in Section 5.1.1. The figure summarizes the main computational steps, from textual Learning Outcomes to the generation of asymmetric similarity scores.

To evaluate the degree of alignment between the first version of the *learning outcomes similarity* algorithm and human judgement, a comparative empirical study was conducted in which automatically generated similarity values were compared with evaluations provided by domain experts. The aim of the study was not to assess performance in an absolute sense, but rather to analyse the extent to which the algorithm is able to reproduce, or deviate from, the ways in which human evaluators interpret relationships between

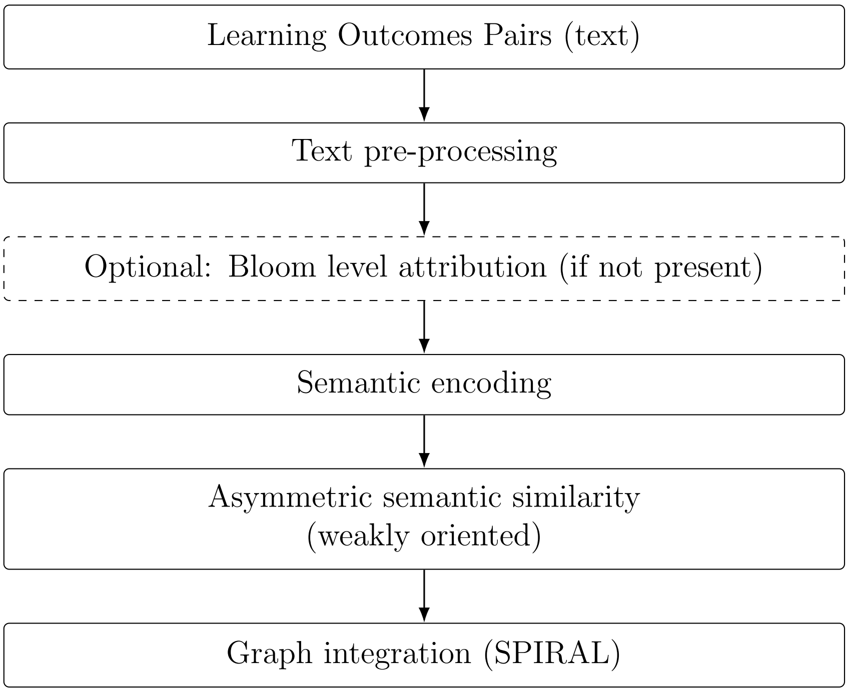

Figure 5.1: Methodological workflow of the first algorithmic version for inferring similarity-based relations among Learning Outcomes. The pipeline computes asymmetric semantic similarity scores that depend on the ordering of the Learning Outcome pairs, but do not encode fully directional (prerequisite) relationships. The resulting relations are integrated into the graph-based representation of the SPIRAL model.

Learning Outcomes, highlighting systematic patterns of agreement and disagreement. The study was carried out in the domains of *mathematics* and *physics*, which were selected as representative of structured disciplinary areas characterised by a strong conceptual component and a clear hierarchical organisation of content. In particular, the Learning Outcomes in mathematics belong to the domain of *calculus*, while those in physics refer to the domain of *kinematics*, ensuring conceptual coherence within each discipline and making the analysis of prerequisite, progression, and generalisation relationships more meaningful. In addition, the choice of these domains was also motivated by practical considerations, as they made it easier to identify disciplinary experts willing to take part in the experimentation, thus ensuring the collection of qualified and methodologically reliable human evaluations. The dataset used in the study was constructed starting from a set of **30 Learning Outcomes in mathematics** and **30 Learning Outcomes in physics**. From each disciplinary set, all possible ordered pairs of Learning Outcomes were generated, resulting in a total of **900 pairs for each domain** (Table 5.1: composition of the complete dataset). This construction allows for an exhaustive exploration of the space of potential relationships between Learning Outcomes within a single disciplinary domain.

Table 5.1: Complete dataset of Learning Outcomes used in the study (Mathematics–Calculus and Physics–Cinematic), as provided in the source CSV files.

id	**Context**	**Subtopic**	**Bloom's Level**	**Learning Outcome**
1	Mathematics	Calculus	Remember	List the fundamental rules of differentiation.
2	Mathematics	Calculus	Remember	Define the concept of a function limit.
3	Mathematics	Calculus	Remember	Identify the properties of continuous functions.
4	Mathematics	Calculus	Remember	Recall the product rule formula.
5	Mathematics	Calculus	Remember	Name the main theorems of integral calculus.
6	Mathematics	Calculus	Understand	Explain the geometric meaning of the derivative.
7	Mathematics	Calculus	Understand	Interpret the concept of area under a curve.
8	Mathematics	Calculus	Understand	Summarize the differences between differentiation and integration.

id	Context	Subtopic	Bloom's Level	Learning Outcome
9	Mathematics	Calculus	Understand	Describe how a function changes based on its derivative.
10	Mathematics	Calculus	Understand	Classify types of discontinuities.
11	Mathematics	Calculus	Apply	Apply Hospital's rule to calculate a limit.
12	Mathematics	Calculus	Apply	Solve an optimization problem using derivatives.
13	Mathematics	Calculus	Apply	Use the definite integral to calculate area.
14	Mathematics	Calculus	Apply	Prove the continuity of a function at a point.
15	Mathematics	Calculus	Apply	Calculate the derivative of a composite function.
16	Mathematics	Calculus	Analyse	Analyse the asymptotic behaviour of a function.
17	Mathematics	Calculus	Analyse	Compare two methods of integration.
18	Mathematics	Calculus	Analyse	Break down a function into parts to facilitate integration.
19	Mathematics	Calculus	Analyse	Determine the relative maxima and minima.
20	Mathematics	Calculus	Analyse	Examine the effect of the second derivative on concavity.
21	Mathematics	Calculus	Evaluate	Justify the choice of an integration method.
22	Mathematics	Calculus	Evaluate	Evaluate the effectiveness of a mathematical model based on calculus.
23	Mathematics	Calculus	Evaluate	Argue the correctness of a proof.
24	Mathematics	Calculus	Evaluate	Critique a common error in limit calculations.
25	Mathematics	Calculus	Evaluate	Defend the use of calculus in an applied context.
26	Mathematics	Calculus	Create	Design a real-world problem solvable with calculus.

id	Context	Subtopic	Bloom's Level	Learning Outcome
27	Mathematics	Calculus	Create	Formulate a function that models a physical phenomenon.
28	Mathematics	Calculus	Create	Construct an exercise requiring the use of derivatives and integrals.
29	Mathematics	Calculus	Create	Develop a strategy to teach the concept of a limit.
30	Mathematics	Calculus	Create	Invent an application of calculus in economics.
31	Physics	Cinematic	Remember	List the equations of uniform linear motion.
32	Physics	Cinematic	Remember	Define velocity and acceleration.
33	Physics	Cinematic	Remember	Identify the SI units for kinematics.
34	Physics	Cinematic	Remember	Recall the formula for uniformly accelerated motion.
35	Physics	Cinematic	Remember	Name the types of motion in kinematics.
36	Physics	Cinematic	Understand	Explain the difference between average and instantaneous velocity.
37	Physics	Cinematic	Understand	Interpret a space-time graph.
38	Physics	Cinematic	Understand	Summarize the characteristics of projectile motion.
39	Physics	Cinematic	Understand	Describe the physical meaning of negative acceleration.
40	Physics	Cinematic	Understand	Classify motions based on trajectory.
41	Physics	Cinematic	Apply	Apply the equations of motion to calculate distance traveled.
42	Physics	Cinematic	Apply	Solve a free fall problem.
43	Physics	Cinematic	Apply	Use a graph to determine instantaneous velocity.
44	Physics	Cinematic	Apply	Calculate the flight time of a projectile.
45	Physics	Cinematic	Apply	Determine the position of an object at a given time.

id	Context	Subtopic	Bloom's Level	Learning Outcome
46	Physics	Cinematic	Analyse	Analyse the motion of an object on an inclined plane.
47	Physics	Cinematic	Analyse	Compare two trajectories in terms of acceleration.
48	Physics	Cinematic	Analyse	Break down a two-dimensional motion into its components.
49	Physics	Cinematic	Analyse	Examine the effect of air resistance on motion.
50	Physics	Cinematic	Analyse	Evaluate velocity changes over a time interval.
51	Physics	Cinematic	Evaluate	Justify the use of a kinematic model in an experiment.
52	Physics	Cinematic	Evaluate	Evaluate the accuracy of an acceleration measurement.
53	Physics	Cinematic	Evaluate	Argue the choice of a reference frame.
54	Physics	Cinematic	Evaluate	Critique a conceptual error in a kinematics problem.
55	Physics	Cinematic	Evaluate	Defend the use of a graphical approach for motion analysis.
56	Physics	Cinematic	Create	Design an experiment to measure velocity.
57	Physics	Cinematic	Create	Formulate a problem involving accelerated motion.
58	Physics	Cinematic	Create	Construct a graph representing complex motion.
59	Physics	Cinematic	Create	Develop a teaching activity on kinematics.
60	Physics	Cinematic	Create	Invent an application of kinematics in everyday life.

Since a manual evaluation of all generated pairs was not operationally feasible, a subset of Learning Outcome pairs was selected for comparison with human judgement. The pairs were randomly extracted from the complete dataset and evaluated by approximately ten assessors, who were asked to rate, on a five-point Likert scale, the extent to which the acquisition of the first Learning Outcome could be considered equivalent to the acquisition of the second one.

Overall, 106 pairs in the mathematics domain and 165 pairs in the physics domain were submitted for human evaluation. When multiple assessments were collected for the same pair, the corresponding scores were aggregated by computing their average, which was used as the reference human judgement for the pair under consideration. For the purpose of aggregation, ratings provided by assessors who reported a low level of confidence in the expressed judgement—requested for each evaluated pair—were excluded.

The comparison between automated semantic similarity and human judgement was conceived as an exploratory analysis aimed at understanding the behaviour of the first formulation of the algorithm, rather than as a validation process against an absolute reference. In this context, human judgement is not assumed as a ground truth, but rather as a complementary measure, grounded in a cognitive process of a different nature from the computational one. Human evaluation of similarity between Learning Outcomes incorporates elements that go beyond textual analysis alone, including implicit knowledge related to the disciplinary domain, the instructional role of learning outcomes, and their positioning within a learning pathway. By contrast, automatically computed similarity relies exclusively on linguistic and semantic information extracted from the textual formulation of learning outcomes, following a reproducible approach that is independent of the specific application context.

In light of these differences, the expert-evaluated subsample was used to investigate the degree of alignment between the two measures and to identify recurring patterns of convergence and divergence. From this perspective, discrepancies between human evaluations and algorithmic values are not interpreted as errors, but as informative signals that highlight intrinsic limitations of a purely text-based approach and help guide subsequent extensions of the model. This methodological setting therefore allows the comparison with human judgement to be used as a tool for critically analysing the behaviour of the algorithm, providing qualitative and quantitative indications of the types of semantic relations it is able to capture effectively, as well as those that require enrichment through cognitive, ontological, or contextual information. The empirical evaluation of this formulation, discussed in the following sections, highlights both its strengths and its limitations, motivating a subsequent revision of the algorithm in which semantic and cognitive components are treated separately.

Results in the Mathematics Domain

On the basis of the methodological framework described in the previous section, the analysis of the results for the mathematics domain was conducted by comparing, for each pair of Learning Outcomes included in the expert-evaluated subsample, the similarity value produced by the first version of the algorithm with the corresponding human judgement, normalized to the interval $[0, 1]$. Here, S_a denotes the similarity score computed automatically by the algorithm, while $S_h^{(01)}$ represents the human similarity judgement expressed on the Likert scale and subsequently rescaled to the unit interval. The difference between the two measures, defined as $\Delta = S_h^{(01)} - S_a$, constitutes the main variable considered in the following analysis. Accordingly, the difference Δ is not interpreted as a measure of algorithmic error, but as an indicator of systematic tendencies in the way semantic and cognitive relations are differently weighted by human experts and by the computational model.

Considering the set of 76 Learning Outcome pairs evaluated in the mathematics domain, the distribution of Δ exhibits an overall positive tendency, with a mean value of 0.12 and a median value of 0.07. This result indicates that, on average, the algorithm tends to underestimate semantic similarity with respect to human expert judgement. The distribution is also right-skewed, suggesting the presence of a limited number of pairs for which the underestimation is particularly pronounced, alongside many observations characterized by relatively small differences. The distribution of the differences is shown in Figure 5.2, where a substantial concentration of values close to zero can be observed.

The purpose of the statistical analysis is therefore not to assess performance in a predictive sense, but to characterise the alignment and misalignment patterns between algorithmic similarity estimates and human judgement, with emphasis on systematic effects over individual discrepancies.

The Wilcoxon signed-rank test, applied to assess whether the median of the differences is significantly different from zero, confirms the presence of a systematic bias (W = 879, $p < 0.01$), indicating that the observed discrepancy between algorithmic similarity and human judgement cannot be attributed to random variation. The analysis of bootstrap confidence intervals provides a more nuanced interpretation of this result: while the 95% confidence interval for the mean of Δ excludes zero, the interval associated with the median includes values close to zero, suggesting that the underestimation, although statistically significant on average, does not occur uniformly across all evaluated pairs.

From a practical perspective, the analysis of agreement thresholds shows

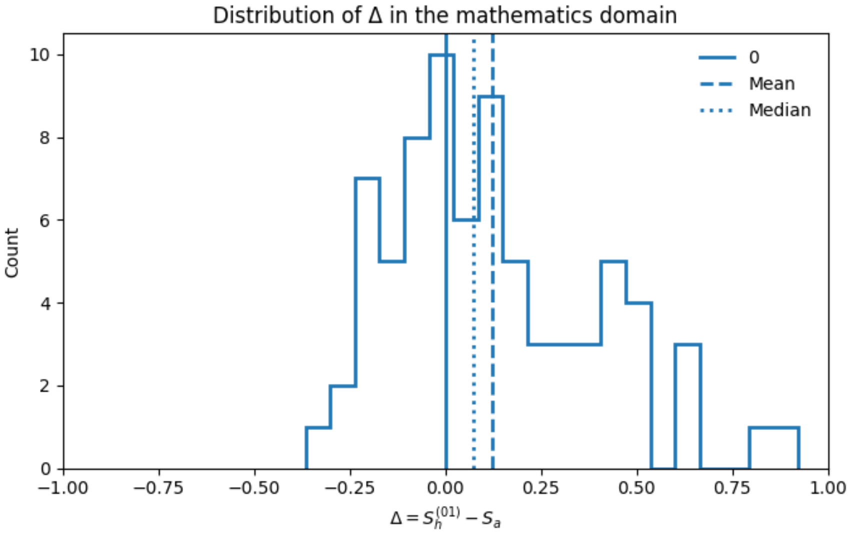

Figure 5.2: Distribution of $\Delta = S_h^{(01)} - S_a$ for the mathematics domain. The vertical lines indicate zero difference, mean difference, and median difference.

that approximately 41% of the pairs exhibit a difference smaller than half a Likert scale level, and more than 68% of the pairs fall within one Likert level. This indicates that, in most cases, the algorithm produces similarity estimates that are reasonably close to human judgement, despite a systematic tendency toward more conservative values.

To better understand the origin of this tendency, the analysis was refined by introducing the cognitive level of Bloom associated with each Learning Outcome. First, pairs were divided according to whether the two Learning Outcomes belonged to the same Bloom level or to different levels. The results show that, for pairs within the same cognitive level, the average difference between human judgement and algorithmic similarity is close to zero and characterized by reduced variability. In contrast, pairs involving different Bloom levels display a more pronounced systematic underestimation, which accounts for most of the global bias observed in the mathematics domain.

A more detailed analysis was then conducted by explicitly considering pairs of Bloom levels. The heatmap of mean differences for each combination of cognitive levels in the mathematics domain is reported in Figure 5.3, while the corresponding distribution of counts is shown in Figure 5.4. The joint interpretation of these figures highlights that the alignment between algorithm and human judgement is particularly high along the diagonal, corresponding to comparisons between Learning Outcomes at the same Bloom level, especially for lower and intermediate cognitive levels where empirical support is stronger. Larger positive differences emerge instead for comparisons between adjacent or moderately distant levels, particularly between lower and intermediate levels, suggesting that the algorithm struggles to capture relations of cognitive continuity or progression that are recognized by human experts.

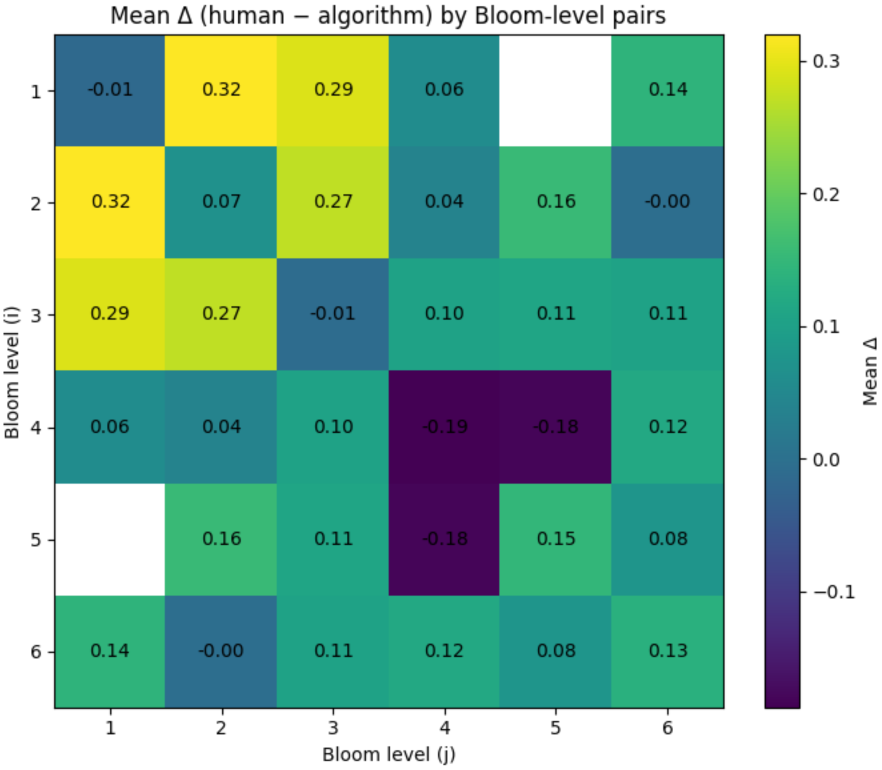

Figure 5.3: Heatmap of mean differences $\Delta = S_h^{(01)} - S_a$ for pairs of Bloom levels in the mathematics domain. Positive values indicate underestimation by the algorithm with respect to human judgement.

Overall, the results for the mathematics domain indicate that the first version of the algorithm exhibits a conservative behaviour: it is able to estimate similarity accurately when Learning Outcomes are cognitively comparable, but it tends to underestimate similarity in the presence of inter-level relations, where the connection between outcomes is more functional or ontological than purely textual.

Results in the Physics Domain

In order to assess the generality of the patterns observed in the mathematics domain, the same analytical procedure was applied to the physics

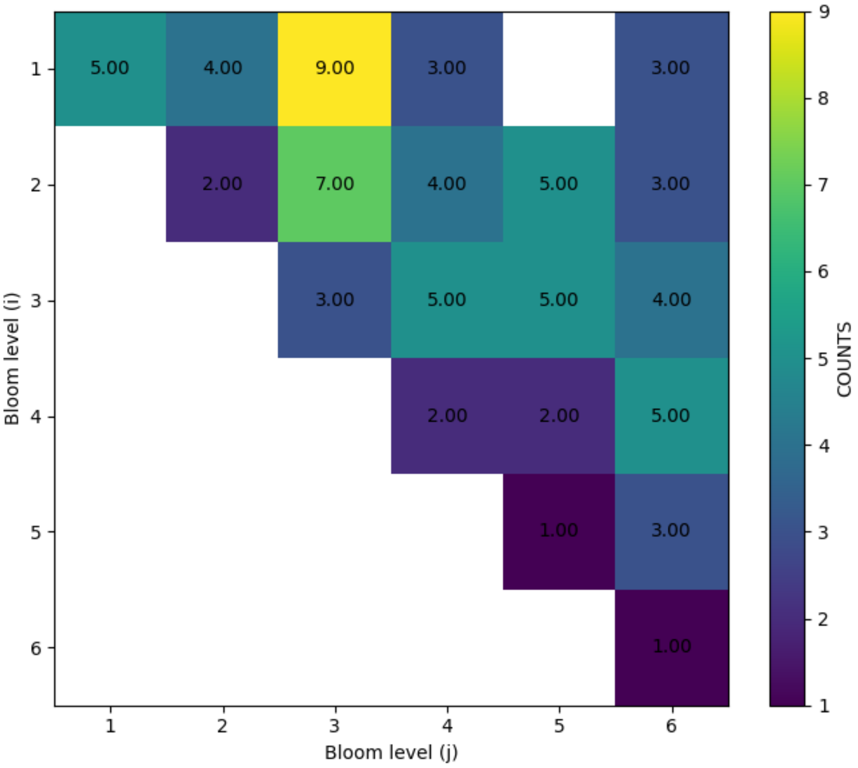

Figure 5.4: Distribution of the number of evaluated Learning Outcome pairs across Bloom-level combinations in the mathematics domain.

domain, using the subsample of 135 Learning Outcome pairs evaluated by experts. As in the previous case, the difference between normalized human judgement and algorithmic similarity, $\Delta = S_h^{(01)} - S_a$, was adopted as the reference variable.

At a global level, the guarantees results for the physics domain show a more pronounced underestimation of semantic similarity by the algorithm than that observed for mathematics. The distribution of Δ presents a mean value of 0.21 and a median value of 0.25, corresponding to a full level of the original Likert scale. The Wilcoxon signed-rank test confirms the strong statistical significance of this discrepancy (W = 1820, $p < 10^{-8}$), indicating the presence of a systematic bias that cannot be attributed to chance. The 95% bootstrap confidence intervals for both the mean and the median exclude zero, suggesting that, in the physics domain, the underestimation is not only significant on average but also consistent at the central tendency level. The distribution of the differences is shown in Figure 5.5. From the standpoint of practical agreement, the threshold analysis reveals a lower level of align-

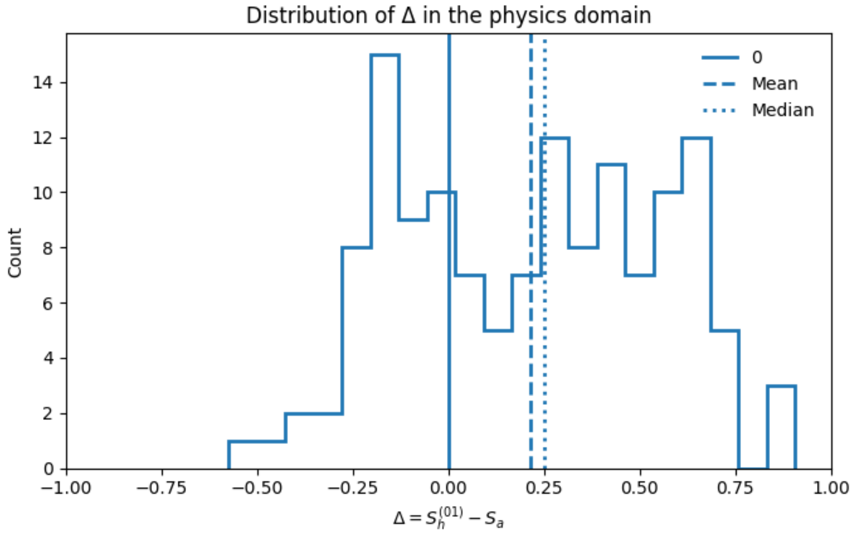

Figure 5.5: Distribution of $\Delta = S_h^{(01)} - S_a$ for the physics domain. The vertical lines indicate zero difference, mean difference, and median difference.

ment than that observed in mathematics. Only 21.5% of the pairs exhibit a difference smaller than half a Likert level, and less than half of the pairs fall within one Likert level. This indicates that, in the physics domain, discrepancies between human judgement and algorithmic similarity are generally larger and more frequent.

The Bloom-level analysis reveals a markedly different behaviour from that observed in mathematics. First, the comparison between pairs belonging to the same Bloom level and pairs involving different levels does not yield statistically significant differences. In particular, the algorithmic underestimation is also present in intra-level comparisons.

A more fine-grained analysis based on the distance between Bloom levels further confirms the absence of a monotonic relationship between cognitive distance and the difference Δ. The heatmap of mean differences for pairs of Bloom levels in the physics domain is reported in Figure 5.6, while the corresponding distribution of counts is shown in Figure 5.7. Positive values of Δ are distributed across most combinations of levels, including the diagonal, indicating that underestimation is not confined to inter-level comparisons. This behaviour is corroborated by the global statistical analysis, which does not detect significant differences between groups defined by Bloom distance, nor a significant correlation between Δ and cognitive distance.

It is also worth noting that, in the physics domain, experts reported on average a lower level of confidence in assigning Likert-scale similarity val-

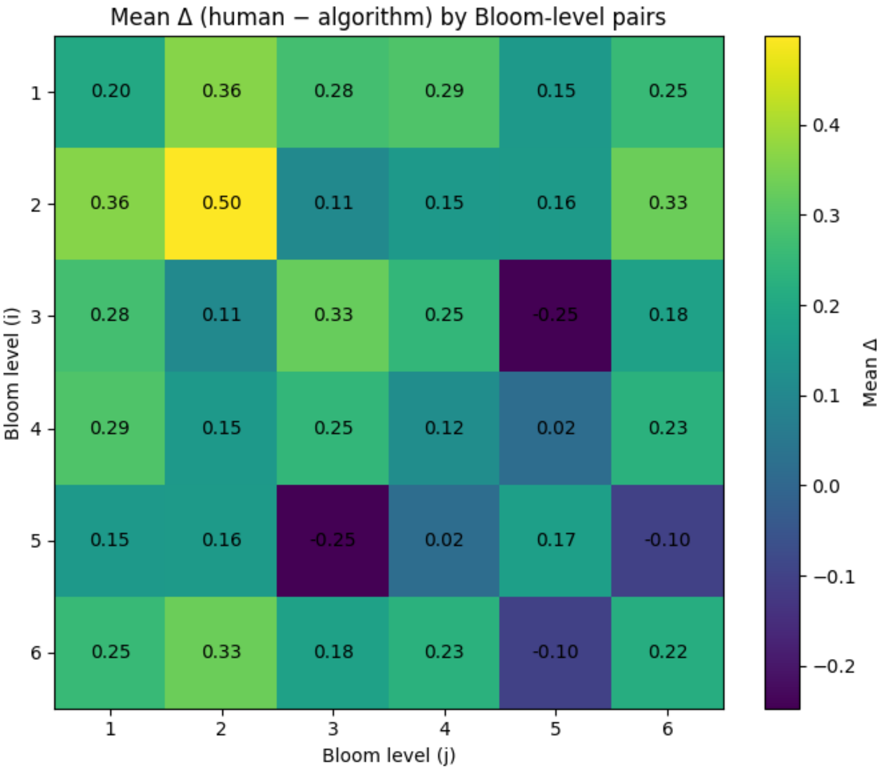

Figure 5.6: Heatmap of mean differences $\Delta = S_h^{(01)} - S_a$ for pairs of Bloom levels in the physics domain.

ues than in the mathematics domain. Although this aspect is not directly incorporated into the quantitative analysis of differences, it provides an important interpretative element, suggesting a higher intrinsic uncertainty in the assessment of semantic similarity between physics Learning Outcomes.

Overall, the results for the physics domain suggest that the underestimation of semantic similarity by the first version of the algorithm is not primarily associated with cognitive distance between Learning Outcomes, but rather reflects a more general mismatch between textual similarity and expert judgement. Unlike mathematics, where the bias is strongly structured with respect to Bloom levels, in physics the algorithm tends to underestimate similarity even in intra-level comparisons, indicating that experts recognize semantic and functional relations that are not adequately captured by a purely linguistic approach.

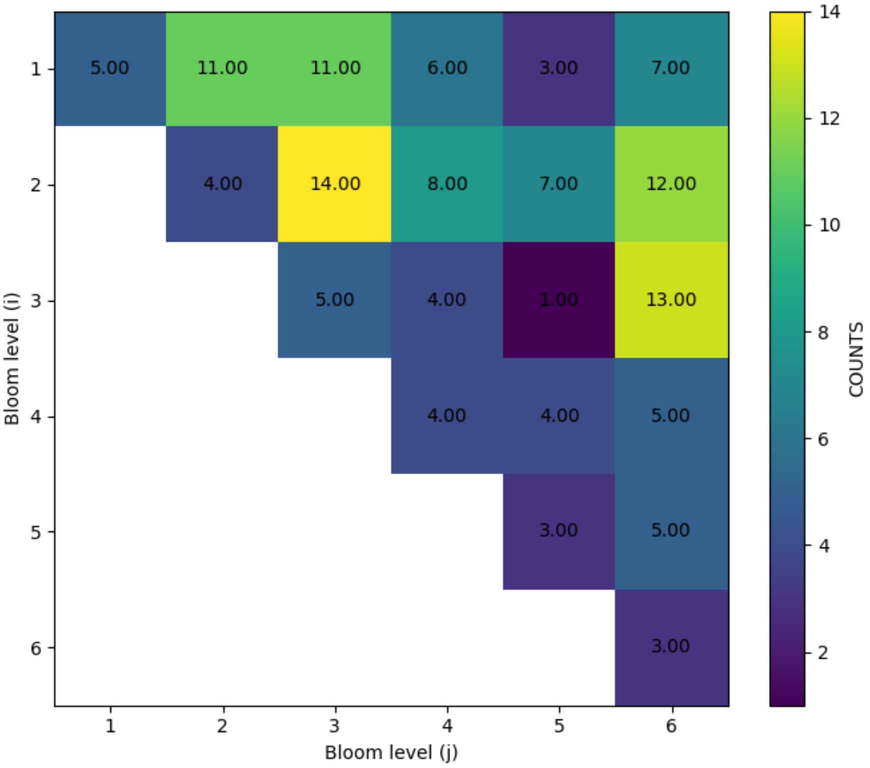

Figure 5.7: Distribution of the number of evaluated Learning Outcome pairs across Bloom-level combinations in the physics domain.

Comparative Discussion and Implications

The comparison between the two domains reveals distinct yet coherent behaviours: in the mathematics domain, the discrepancy between algorithmic similarity and human judgement is strongly structured by Bloom's cognitive levels, whereas in the physics domain such discrepancies appear more diffuse and cannot be explained solely in terms of cognitive distance. These findings suggest that a single, unitary similarity score is insufficient to capture and interpret the complexity of relationships between Learning Outcomes across domains. In particular, the early integration of semantic similarity and cognitive distance, while conceptually coherent, limits the interpretability of the observed discrepancies. This evidence motivates a reformulation of the algorithm in which the cognitive component, related to Bloom level, and the semantic component, related to textual content, are treated as distinct and explicitly interpretable dimensions, as discussed in Section 5.1.3.

5.1.2 The Comparison between Algorithm and LLM

In addition to the comparison between algorithmic similarity and human judgement, a further analysis was conducted to compare the proposed algorithm with a Large Language Model (LLM), namely ChatGPT, applied to the full set of Learning Outcome pairs. This comparison is not intended to establish a hierarchy between the two approaches, nor to treat one of them as a ground truth. Rather, it aims to characterise similarities and systematic differences between two fundamentally different paradigms: on the one hand, a transparent and controllable algorithm explicitly designed to model educational relationships, and on the other hand, a generative language model optimised to capture semantic relations from large-scale textual data, but lacking an explicit representation of cognitive or instructional structures.

For each pair of Learning Outcomes, the difference between the similarity value produced by the LLM and that produced by the algorithm was computed as $\Delta = S_{\text{LLM}} - S_a$. The analysis was conducted separately for the mathematics and physics domains, considering the full set of available pairs in each domain.

In the mathematics domain, the distribution of Δ exhibits an overall positive tendency, with a mean value of approximately 0.07 and a median value of approximately 0.10. This indicates that the LLM tends to assign systematically higher similarity values than the algorithm, although the average magnitude of the difference remains limited. The distribution is asymmetric, with a tail of more extreme negative values, indicating that in a limited number of cases the LLM assigns a substantially lower similarity than the algorithm. The Wilcoxon signed-rank test confirms that the median difference is significantly different from zero, and the bootstrap confidence intervals for both the mean and the median exclude zero, suggesting the presence of a systematic offset between the two approaches. From a practical perspective, the threshold analysis shows that nearly 90% of the pairs exhibit a difference smaller than one level of the Likert scale, indicating a high overall compatibility between the similarity estimates produced by the LLM and those produced by the algorithm.

A substantially analogous pattern emerges in the physics domain. Also in this case, both the mean and the median of the differences are positive and closely aligned with the values observed in mathematics, and the distribution shows a marked asymmetry towards more extreme negative values. Statistical testing and bootstrap confidence intervals again confirm the significance of the difference, while the threshold analysis reveals levels of agreement almost identical to those observed for mathematics. In particular, the proportion of pairs for which the difference between LLM and algorithm remains within one Likert scale level exceeds 85%.

A particularly relevant aspect of these results is their stability across the two disciplinary domains. Unlike the comparison between algorithmic similarity and human judgement, where discrepancies were strongly domain-dependent and influenced by the cognitive structure of the Learning Outcomes, the comparison between the algorithm and the LLM reveals a remarkably consistent behaviour across mathematics and physics. This suggests that the LLM primarily operates as a domain-agnostic semantic similarity estimator, sensitive to linguistic and contextual relations between Learning Outcome statements, but largely insensitive to differences of a cognitive or instructional nature.

Overall, these findings indicate that the LLM and the algorithm produce broadly compatible similarity estimates, despite a systematic difference in calibration. The LLM tends to assign higher similarity values in a consistent manner, whereas the algorithm adopts a more conservative estimation strategy. This discrepancy does not appear to be associated with disciplinary particularities, thereby reinforcing the hypothesis that the primary function of the LLM is to capture textual semantic similarity rather than to model cognitive or instructional relationships. This evidence further supports the distinction between semantic and cognitive components introduced in the following section and clarifies the potential role of LLMs as supportive, but not substitutive, tools in educational modelling processes.

5.1.3 The Second Version of the Algorithm

Building on the results obtained with the first formulation of the algorithm, a second version was developed with the aim of improving the interpretability of the learning outcomes similarity computation process and enabling a more informed integration of a human-in-the-loop perspective. In the first version, semantic similarity and cognitive distance, expressed through the Bloom's taxonomy level $\mathcal{L}(LO)$, were combined early into a single directional score. While this formulation offers a compact representation of the oriented nature of relationships between Learning Outcomes, the empirical analysis highlighted that such an early integration obscures the distinct contribution of semantic and cognitive factors. In particular, the results showed that cognitive distance plays a structurally different role across domains, contributing to systematic underestimation effects in some contexts while being less explanatory in others. These findings indicate that a unified score is insufficient to capture the complexity of similarity relations and motivate a reformulation in which semantic similarity and cognitive distance are treated as separate, explicitly interpretable components.

The second algorithmic approach therefore introduces an explicit separation between the semantic and the cognitive components, with the goal of making the algorithm's behaviour more readable and controllable. On the one hand, a semantic similarity measure based on textual embeddings is computed; on the other hand, the distance between the cognitive levels of the Learning Outcomes involved is estimated independently. This distinction enables the construction of more explicit and objective relationships between Learning Outcomes. In particular, pairs of Learning Outcomes characterised by the same cognitive level ($\Delta\mathcal{L} = 0$) can be interpreted as potential equivalence relations, whereas negative differences ($\Delta\mathcal{L} < 0$) indicate prerequisite relations, in which the achievement of LO_i can be considered functional to the achievement of LO_j. Within this framework, the *strength* of the relation is not determined by cognitive distance, but can be associated with the value of semantic textual similarity sem_{sim}, which provides a graded indication of the degree of conceptual overlap between the two Learning Outcomes. Operationally, the second version of the algorithm proceeds by computing semantic similarity and cognitive distance between each ordered pair of Learning Outcomes as two independent quantities. Figure 5.8 illustrates the methodological workflow of the second version of the similarity algorithm, introduced in Section 5.1.3. Compared to the first version, this approach explicitly integrates cognitive constraints to infer directional similarity relations.

The difference in Bloom levels is used to characterise the structural nature of the relation (e.g., equivalence or prerequisite), while the semantic similarity score provides a graded indication of the conceptual overlap between the outcomes involved. This separation makes it possible to infer relations that are both cognitively grounded and semantically interpretable, without collapsing these two dimensions into a single composite value, and enables the construction of similarity-based relations that remain interpretable across domains. From a methodological perspective, this separation enables the construction of similarity-based relations that remain interpretable across domains, addressing one of the main limitations observed in the first algorithmic formulation.

A further advantage of this formulation lies in the fact that differences between Bloom levels constitute a *fixed and context-independent* property, whereas semantic similarity is more strongly influenced by the linguistic formulation of the outcomes and by the reference domain. In this sense, the role of the *human-in-the-loop* is not to modify the cognitive structure of the inferred relations, but to support their interpretation and validation, particularly in cases where discrepancies emerge between textual semantic similarity and underlying conceptual or ontological proximity. The algorithm can therefore be regarded as a support tool for instructional design, capable

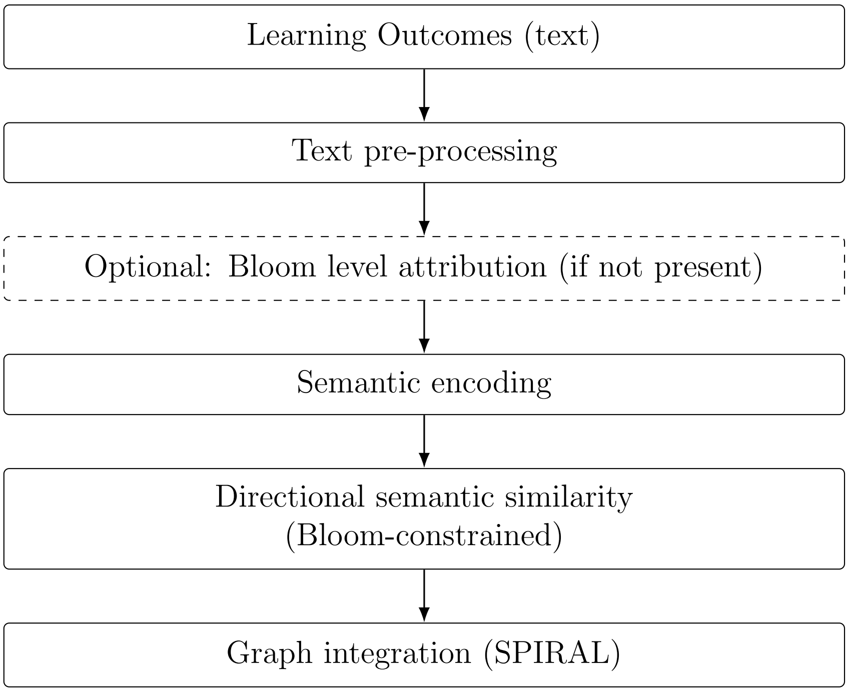

Figure 5.8: Methodological workflow of the second algorithmic version for inferring similarity-based relations among Learning Outcomes. The shared preprocessing and semantic encoding pipeline is optionally extended with automatic Bloom level attribution. Cognitive annotations are then used to constrain the similarity computation, resulting in fully directional similarity relations that are integrated into the graph-based representation of the SPIRAL model.

of making explicit the tensions between semantic and cognitive dimensions, while leaving to human expertise the task of contextualising and refining the proposed relationships in light of specific educational goals.

Formally, let $\mathcal{LO} = \{LO_1, \ldots, LO_n\}$ denote the set of Learning Outcomes under consideration. For each ordered pair (LO_i, LO_j) with $LO_i \neq LO_j$, the second version of the algorithm computes two independent quantities:

- ▷ a semantic similarity score

  $$\mathrm{sem}_{\mathrm{sim}} : \mathcal{LO} \times \mathcal{LO} \to [0, 1],$$

  obtained from the comparison of the textual embeddings associated with LO_i and LO_j;

- ▷ a cognitive level difference

  $$\Delta\mathcal{L}(LO_i, LO_j) = \mathcal{L}(LO_j) - \mathcal{L}(LO_i),$$

The algorithm introduces a candidate relation between LO_i and LO_j only if $\mathrm{sem}_{\mathrm{sim}}(LO_i, LO_j) \geq \rho_{\min}$, with $\rho_{\min} = 0.5$, in order to exclude weak or pedagogically irrelevant semantic associations. No relation is generated for similarity values below this threshold. As noted in the literature, embedding-based semantic similarity models do not define absolute or universal thresholds, as similarity scores are continuous and their interpretation is inherently task- and domain-dependent [56]. Accordingly, the threshold values adopted in this work are not intended to represent intrinsic semantic boundaries, but rather operational cut-offs chosen to support specific stages of the methodological pipeline.

Given a pair (LO_i, LO_j) satisfying this condition, the structural nature of the relation is determined by the sign of $\Delta\mathcal{L}$, while its strength is associated with the value of $\mathrm{sem}_{\mathrm{sim}}$. Specifically:

- ▷ if $\Delta\mathcal{L}(LO_i, LO_j) = 0$, the relation is interpreted as a similarity or equivalence relation between Learning Outcomes at the same cognitive level;

- ▷ if $\Delta\mathcal{L}(LO_i, LO_j) < 0$, the relation is interpreted as a potential prerequisite relation, in which the achievement of LO_i may support the achievement of LO_j;

- ▷ if $\Delta\mathcal{L}(LO_i, LO_j) > 0$, no relation is introduced, as this configuration would contradict the assumed cognitive progression.

Within each admissible structural configuration, the semantic similarity score sem_{sim} provides a graded indication of the degree of conceptual overlap between the two Learning Outcomes and is subsequently used to discriminate between weak semantic associations and strong near-paraphrastic relations. Thresholds applied to sem_{sim} are therefore interpreted as operational design parameters and not as universal semantic constants, and serve to identify candidate relations that require different levels of pedagogical attention and validation. In particular, a lower threshold of 0.5 was introduced to filter out pairs exhibiting weak or marginal semantic relatedness, ensuring that only Learning Outcome pairs with a minimum level of shared semantic content are retained for further analysis. Conversely, a higher threshold of 0.85 was used to identify pairs that can be reasonably interpreted as strongly similar or quasi-equivalent, and therefore suitable to support the construction of alternative and equivalent learning paths.

This formulation allows semantic and cognitive dimensions to be inspected independently, making the behaviour of the algorithm transparent and supporting a principled integration of human judgement in the validation of the inferred relations.

5.2 Model Representation and Metrics

The similarity relations inferred through the algorithms described in the previous section constitute the main output of the computational process, but they acquire their full meaning only when integrated into a structured model representation. For this reason, the present section focuses on the graph-based representation of the SPIRAL model and on the metrics introduced to analyze its structural properties, with the aim of assessing how similarity relations contribute to the configuration of learning paths and to their potential for personalization.

5.2.1 Rationale for a Graph-Based Representation of Learning Paths

The adoption of a graph-based representation for learning paths within the SPIRAL model is motivated by a view of curricula and learning processes as structured systems of interrelated elements that extend beyond linear sequences of instructional units. [55]. Throughout this thesis, learning is conceived as a process that unfolds through relationships among concepts, learning outcomes, and instructional activities, where progression and coherence depend on how these elements are connected. A formal representation capable of explicitly capturing such relationships is therefore required in order to support both pedagogical analysis and computational evaluation.

In this perspective, graph-based models offer a well-established formalism for representing complex relational structures. By modelling learning elements as nodes and their dependencies as edges, graphs make it possible to externalize and inspect the underlying structure of a curriculum or course. This approach aligns with perspectives that interpret curricula as complex systems in which meaning making is supported by connectivity, and where the task of design includes making relationships explicit [55].

Insights from the theory of complex networks further support the suitability of this representation. Empirical studies of real-world networks show that many natural, social, and informational systems exhibit heterogeneous structures, where connectivity is unevenly distributed and certain elements assume a structurally central role [51, 54]. In educational settings, analogous structures may emerge when specific learning outcomes or concepts act as pivotal elements that connect multiple parts of a curriculum. A graph-based representation enables such structural properties to be made explicit and analysed.

Within digital learning environments and personalized education, graph-based models are increasingly used to represent knowledge structures and support the planning of learning trajectories. In particular, recent work on personalized learning path recommendation explicitly combines knowledge graphs with learner modelling to generate or select suitable sequences of knowledge points and resources [30]. This is especially relevant when the goal is not to prescribe a single optimal path, but to represent a space of admissible alternatives under pedagogical constraints and learner-dependent conditions.

The relevance of graph-based modelling is also emphasized in the Artificial Intelligence in Education literature, where personalization is framed as a data-informed process that benefits from structured representations and from the integration of learner information with content and progression models [40]. In this sense, graphs provide a common formalism to connect educational design elements, learner-related information, and analytic methods in an interpretable way.

Against this background, the adoption of a graph-based representation in the SPIRAL model serves a dual purpose. From a pedagogical standpoint, it supports reflective design by making conceptual and instructional dependencies explicit, thus enabling the inspection of coherence, redundancy, and progression patterns. From a computational standpoint, it provides a formal basis for applying established network measures and algorithms to evaluate and compare alternative learning paths [55]. Crucially, within SPIRAL, graph-based modelling is not intended to automate the design of learning paths; rather, it supports the evaluation of alternative pathways within a pedagogically structured design space initially defined by the educator.

5.2.2 Model Representation

Within the SPIRAL model, the graph-based representation is not conceived as a direct description of a prescribed learning path, but rather as a *structured design space* that makes explicit the pedagogical possibilities defined during the macro-design phase. The graph externalizes and renders inspectable the relational structure underlying a course, showing how Learning Outcomes, Learning Units, and pedagogical constraints combine to delineate a set of admissible learning paths. From this perspective, the graph supports reflective course design and computational analysis, without replacing educator-driven decision-making.

To fulfil this role, the model integrates *three conceptually distinct layers of relationships*: (i) *design-time relations*, explicitly defined by the instructor and expressing strong pedagogical constraints; (ii) *infered relations*, automatically inferred from the semantic and cognitive analysis of Learning Outcomes and interpreted as structural hypotheses nd not as prescriptions; and (iii) *derived relations*, obtained by propagating infered relations to the level of Learning Units in order to support the identification of alternative instructional trajectories. This layered distinction preserves the instructional intentionality of the learning design while enabling the controlled integration of computational tools for analysis, comparison, and personalization.

Within this conceptual framework, the adoption of a graph database is a technical consequence of the underlying modelling choices instead of their starting point. Once a course is conceived as a relational design space in which educational entities and pedagogical relationships play a central role, the use of a technology natively designed to represent nodes and edges becomes a coherent and natural solution. The graph database does not introduce additional conceptual assumptions, but provides an appropriate infrastructure for instantiating, querying, and analysing the model-defined structure while preserving its interpretability and alignment with pedagogical intent.

Nodes. At the level of course modelling, four primary node types are defined: *Course*, *Macro Learning Outcome*, *Micro Learning Outcome*, and *Learning Unit.* Course nodes represent coherent educational offerings. Learning Outcomes describe the knowledge, skills, or competences that learners are expected to acquire and may function as macro outcomes, micro outcomes, or prerequisites. Learning Units represent instructional modules designed to produce exactly one Micro Learning Outcome.

Design-time Relations. Design-time relations are specified explicitly by the instructor during the macro-design phase and constitute strong pedagogical constraints. At course level, the following relations are defined:

- ▷ `Is_Macro_Outcome_Of` (*Macro LO* → *Course*), associating course-level objectives with the course;
- ▷ `Is_Part_Of` (*LU* → *Macro LO*), indicating the contribution of a Learning Unit to a macro objective;
- ▷ `Has_Outcome` (*LU* → *Micro LO*), defining the Learning Outcome produced by a Learning Unit;
- ▷ `Prerequisite_Of` (*LO* → *LU*), encoding mandatory prerequisite conditions for accessing a Learning Unit.

These relations define the normative structure of the course and are never overridden by computational inference.

Infered Relations between Learning Outcomes. Infered relations are defined exclusively between Learning Outcomes and are generated according to the second version of the algorithm described in section 5.1.3. For each ordered pair (LO_i, LO_j), the algorithm produces a semantic similarity score $\text{sem}_{\text{sim}}(LO_i, LO_j)$ and a Bloom level difference $\Delta_B = B(LO_j) - B(LO_i)$. Relations are introduced only if $\text{sem}_{\text{sim}}(LO_i, LO_j) \geq 0.5$.

If $0.5 \leq \text{sem}_{\text{sim}}(LO_i, LO_j) < 0.85$:

- ▷ if $\Delta_B = 0$, a symmetric `Similar_To` relation is introduced;
- ▷ if $\Delta_B > 0$, a directed `Connected_To` $(LO_i \rightarrow LO_j)$ relation is introduced;
- ▷ if $\Delta_B < 0$, no relation is generated.

If $\text{sem}_{\text{sim}}(LO_i, LO_j) \geq 0.85$:

- ▷ if $\Delta_B = 0$, a symmetric `Equivalent_To` relation is introduced;
- ▷ if $\Delta_B > 0$, a directed `Possible_Prerequisite_Of` $(LO_i \rightarrow LO_j)$ relation is introduced and explicitly marked as requiring instructor validation;

- ▷ if $\Delta_B < 0$, no relation is generated.

These relations do not impose mandatory constraints, but provide structured hypotheses to support pedagogical analysis.

Derived Relations between Learning Units. Derived relations are obtained by propagating infered relations defined at Learning Outcome level. Let $LO_i = LO(LU_i)$ and $LO_j = LO(LU_j)$. Then:

- ▷ $LU_i \leftrightarrow LU_j$ `Similar_To` if $LO_i \leftrightarrow LO_j$ are `Similar_To`;
- ▷ $LU_i \rightarrow LU_j$ `Connected_To` if $LO_i \rightarrow LO_j$ are `Connected_To`;
- ▷ $LU_i \leftrightarrow LU_j$ `Equivalent_To` if $LO_i \leftrightarrow LO_j$ are `Equivalent_To`;
- ▷ $LU_i \rightarrow LU_j$ `Probably_Unlocks` if $LO_i \rightarrow LO_j$ are `Possible_Prerequisite_Of`.
- ▷ $LU_i \rightarrow LU_j$ `Unlocks` if $LO_i \rightarrow LO_j$ are connected by a design-time `Prerequisite_Of` relation.

Derived relations never override design-time prerequisites. Their function is to make explicit alternative, conditional, or substitutable instructional trajectories within the pedagogically defined design space.

Table 5.2 provides a consolidated overview of the design-time, computational, and derived relationships adopted in the SPIRAL model, summarizing their level of application, origin, symmetry, and pedagogical role within the graph-based representation.

Table 5.2: Design-time, computational, and derived relationships in the SPIRAL model

Relation	**Level**	**Type**	**Symmetry**	**Role**
`Is_Macro_Outcome_Of`	Macro LO–Course	Design-time	Asymmetric	Defines course-level learning objectives
`Is_Part_Of`	LU–Macro LO	Design-time	Asymmetric	Contribution of a Learning Unit to a macro objective

Relation	**Level**	**Type**	**Symmetry**	**Role**
`Has_Outcome`	LU–Micro LO	Design-time	Asymmetric	Defines the outcome produced by a Learning Unit
`Prerequisite_Of`	LO–LU	Design-time	Asymmetric	Mandatory prerequisite constraint
`Similar_To`	LO–LO	Computation	Symmetric	Semantic affinity at the same Bloom level
`Equivalent_To`	LO–LO	Computation	Symmetric	Interchangeable Learning Outcomes
`Connected_To`	LO–LO	Computation	Asymmetric	Weak semantic association across Bloom levels
`Possible_Prerequisite_Of`	LO–LO	Computation	Asymmetric	Candidate prerequisite (human validation required)
`Similar_To`	LU–LU	Derived	Symmetric	Alternative Learning Units with similar outcomes
`Equivalent_To`	LU–LU	Derived	Symmetric	Substitutable Learning Units
`Connected_To`	LU–LU	Derived	Asymmetric	Conditional instructional dependency

Relation	**Level**	**Type**	**Symmetry**	**Role**
`Unlocks`	LU–LU	Derived	Asymmetric	Deterministic instructional dependency derived from design-time prerequisites
`Probably_Unlocks`	LU–LU	Derived	Asymmetric	Conditional access based on candidate prerequisite

At the instructional level, prerequisite relationships between Learning Units are derived exclusively from design-time prerequisite relationships between Learning Outcomes. Infered relations never override these constraints, but enable the identification of alternative Learning Units producing equivalent or inclusive Learning Outcomes, potentially characterized by different workloads.

The set of nodes and relationships described above constitutes a minimal yet expressive collection of modelling primitives for representing individual courses and their internal learning paths. While sufficiently rich to capture prerequisite structures, equivalences, and alternative trajectories, this set is not intended to be exhaustive. When modelling educational structures at a broader scale, such as curricula or degree programs, additional node types (e.g., programs, semesters, competence frameworks) and relationship types may be introduced according to specific analytical or design requirements. Figure 5.9 illustrates the conceptual schema of the database underlying the SPIRAL model, showing the node types involved and the set of design-time, infered, and derived relations defined among Courses, Macro Learning Outcomes, Learning Units, and Micro Learning Outcomes. Graph relationships may further be characterized by weights encoding contextual or learner-dependent information, such as estimated workload, difficulty, or preference-based indicators. These weights do not affect the pedagogical validity of the underlying structure, but support the evaluation and comparison of alternative learning paths under different conditions. In this sense, weighting mechanisms act as analytical modulators, while the core graph structure preserves instructional intent. From an operational perspective, a course designed according to the SPIRAL model can be instantiated as a directed graph in which nodes correspond primarily to Learning Units and edges encode prerequisite or derived relationships. This representation supports both human interpretation during course design and computational processing for subsequent analysis. Consistent with the principles of the SPIRAL model, the objective is not to replace educator-driven design with automated path construction, but to enable the evaluation and comparison of alternative learning paths relative to a pedagogically structured course initially defined by the instructor. A concrete application of this representation is presented in Section 6.

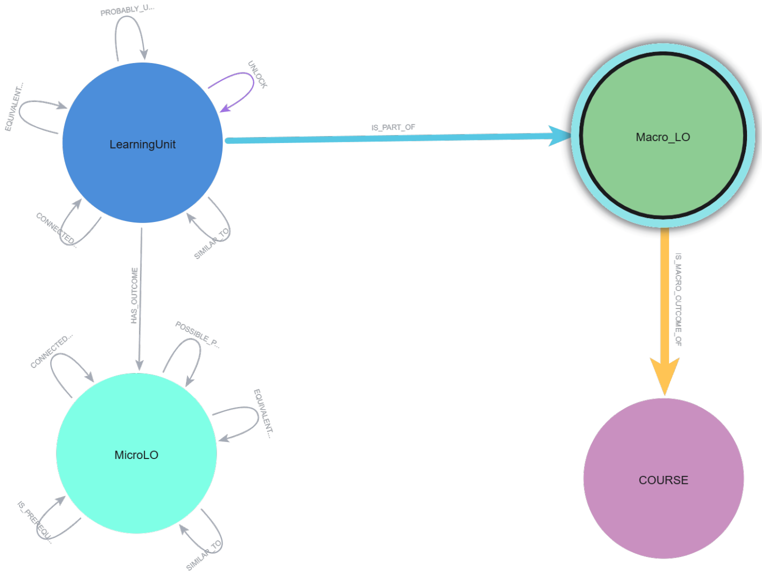

Figure 5.9: Conceptual schema of the graph-based database adopted for the SPIRAL model, showing node types (Course, Macro Learning Outcome, Learning Unit, Micro Learning Outcome) and the corresponding design-time, infered, and derived relations.

5.2.3 Metrics for Graph Analysis

Once learning paths are represented through a graph structure, it becomes possible to analyze their properties by means of metrics derived from network theory. Within the SPIRAL model, these metrics are adopted from an explicitly evaluation-oriented perspective: they are not used to optimize or automatically generate learning paths, but rather to support a structured interpretation of the pedagogical characteristics of designed pathways. In particular, they make it possible to highlight aspects such as coherence, connectivity, and the presence of conceptually central elements. From this perspective, graph analysis metrics function as interpretative tools that can inform both instructional design and personalization support mechanisms.

The metrics considered in this work are drawn from those proposed by O'Meara and Vaidya [55] in their analysis of curricula as networks of concepts, where nodes represent learning elements and edges encode conceptual or instructional relationships. These metrics are selected for their ability to provide a structural reading of learning paths that remains directly interpretable in pedagogical terms, enabling a meaningful connection between formal graph properties and instructional design choices.

A first fundamental metric is the *degree distribution*, which describes how the number of connections is distributed across the nodes of the graph. In an educational context, this metric allows one to observe whether the structure of a course is characterized by many nodes with few connections and a limited number of highly connected nodes. Such nodes can be interpreted as learning outcomes or instructional units that play a central role in the learning path, acting as conceptual or instructional hubs. Analysing the degree distribution therefore supports the identification of key elements that structure the learning path and that, due to their centrality, may require particular attention during course design or revision.

A complementary metric is *betweenness centrality*, which quantifies the extent to which a node lies on shortest paths connecting other pairs of nodes in the graph. Unlike degree-based measures, betweenness does not capture how many connections a node has, but rather how structurally unavoidable it is within the network. In the context of learning paths, nodes with high betweenness centrality act as transitional elements that connect different phases of the course, functioning as bridges between otherwise weakly connected regions of the graph. From a pedagogical perspective, such nodes may represent critical moments in the learning progression, where multiple conceptual or instructional trajectories converge.

A second relevant metric is the *clustering coefficient*, which measures the degree of local interconnection among neighbour nodes. From a pedagogical perspective, a high clustering coefficient can be interpreted as the presence of groups of learning outcomes or learning units that are strongly interconnected, offering learners multiple opportunities to establish connections among related concepts. This property is particularly significant in educational terms, as it reflects the possibility of constructing meaning through multiple and reinforcing relationships, thereby supporting deeper and more flexible understanding.

The *average path length* represents another central metric and indicates the average number of steps required to connect any two nodes in the graph. When applied to learning paths, this metric provides an indication not only of the structural efficiency of the course, but also of the ease with which learners can relate potentially distant concepts or learning outcomes. A relatively low average path length suggests that the structure of the course facilitates knowledge integration and movement across ideas without requiring excessively long or fragmented sequences.

Finally, particular attention is devoted to the identification of *hub nodes*, that is, nodes characterized by a number of connections significantly higher than the average. Within the SPIRAL model, such nodes may be interpreted as learning outcomes or learning units that play a structuring role in the learning path, acting as access points or transition elements between different parts of the course. The presence of hubs is not inherently positive or negative, but rather represents a critical design feature: identifying these nodes supports reflection on their pedagogical relevance, their potential cognitive load, and their placement within the overall learning structure.

Taken together, these metrics enable the description and comparison of different learning path configurations by revealing structural properties that would not emerge from a purely sequential representation. Within the SPIRAL model, they provide the analytical basis for the evaluations presented in the following sections, which focus on the comparison of alternative learning paths and on the support of personalization strategies, while preserving the instructional structure intentionally defined by the educator. Chapter 4 introduced the SPIRAL model from a conceptual and design-oriented perspective, defining its core principles, main components, and the distinction between explicitly designed relationships and inferred relations. Building on this theoretical foundation, Chapter 5 focused on the computational aspects of the model, addressing the algorithms used to infer similarity-based relations among Learning Outcomes, their integration into a graph-based representation, and the metrics adopted to analyse the structural properties of the resulting model. On the basis of this methodological framework, Chapter 6 presents an example of course design using the SPIRAL model, illustrating how the principles, algorithms, and representations introduced in the previous chapters can be applied within a concrete instructional design context.

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Chapter 6

Example of a Course Designed with the SPIRAL Model

This chapter presents a concrete example of course design developed according to the SPIRAL Model. The example refers to the design of a micro-credential focused on the use of the Moodle Learning Management System for educational purposes. The course is conceived as a short yet structured learning experience aimed at supporting teachers, tutors, and trainers in the development of both operational and analytical competencies related to online and blended course management.

6.1 Course Context and Instructional Design

The course is designed as a micro-credential, in line with current European and international trends promoting modular, stackable, and flexible learning opportunities. The target audience primarily consists of educators with limited prior experience in Moodle, although the course progressively addresses more advanced topics related to user management and learning analytics.

From an instructional design perspective, the course follows a progressive and hierarchical structure. It starts from introductory concepts concerning Learning Management Systems and Moodle interface navigation, then moves towards course configuration and structural organization, and finally reaches advanced topics related to monitoring and interpreting learner participation data. Learning outcomes are articulated at both macro and micro levels and are explicitly associated with Bloom's taxonomy, supporting a clear alignment between objectives, activities, and expected cognitive processes.

The design process was supported by a shared planning document developed collaboratively using a structured spreadsheet. The spreadsheet includes general course metadata, macro and micro learning outcomes, learning units, prerequisites, and expected outcomes. The full design document is available at the following link: Design of "ABC of Moodle: Designing and Managing Online Courses"

6.2 Graph-based Representation of the Course

Following the SPIRAL framework, the course structure is represented through a graph-based model. In this representation, Learning Units are modeled as nodes, while design-time prerequisite relations are encoded as directed edges. In particular, the `UNLOCKS` relation represents dependency constraints derived from explicitly defined prerequisite learning outcomes.

Figure 6.1 illustrates the overall structure of the course graph, highlighting the progression from introductory learning units to more advanced analytical units. The visualization represents exclusively design-time relations and provides a comprehensive view of the pedagogical architecture defined within the SPIRAL framework. The resulting graph exhibits a directed acyclic structure, ensuring a coherent and unambiguous learning progression. The main structural properties of the course graph are summarised in Table 6.1. In particular, the graph includes 15 Learning Units connected by 18 design-time `UNLOCKS` relations, with a single entry point and five terminal units.

In the figure, the course entity is represented by the central pink node, which acts as the conceptual anchor of the entire structure. Green nodes correspond to macro Learning Outcomes, organized according to their Bloom taxonomy levels, while blue nodes represent individual Learning Units associated with the course. Orange directed edges encode the `IS_MACRO_OUTCOME_OF` relations linking macro Learning Outcomes to the course, whereas light-blue edges represent `IS_PART_OF` relations connecting Learning Units to their corresponding macro Learning Outcomes.

Design-time prerequisite dependencies between Learning Units are encoded by purple directed edges corresponding to the `UNLOCKS` relation. These edges define the intended learning progression and make explicit the dependency structure governing access to subsequent units. The visual separation between hierarchical relations (course–outcomes–units) and prerequisite relations supports immediate interpretability of both the conceptual organization and the temporal sequencing of the course.

Table 6.1: Structural properties of the course graph (design-time relations).

Indicator	**Value**
Number of Learning Units	15
Number of `UNLOCKS` relations	18
Number of entry points (in-degree = 0)	1
Number of terminal units (out-degree = 0)	5
Number of cycles	0
Maximum path length	10

Overall, the figure provides a synthetic yet expressive representation of the course design, making explicit the interplay between learning outcomes, learning units, and prerequisite constraints. This visualisation supports both design inspection and subsequent analytical exploration, serving as a reference point for the graph-based analyses discussed in the following sections.

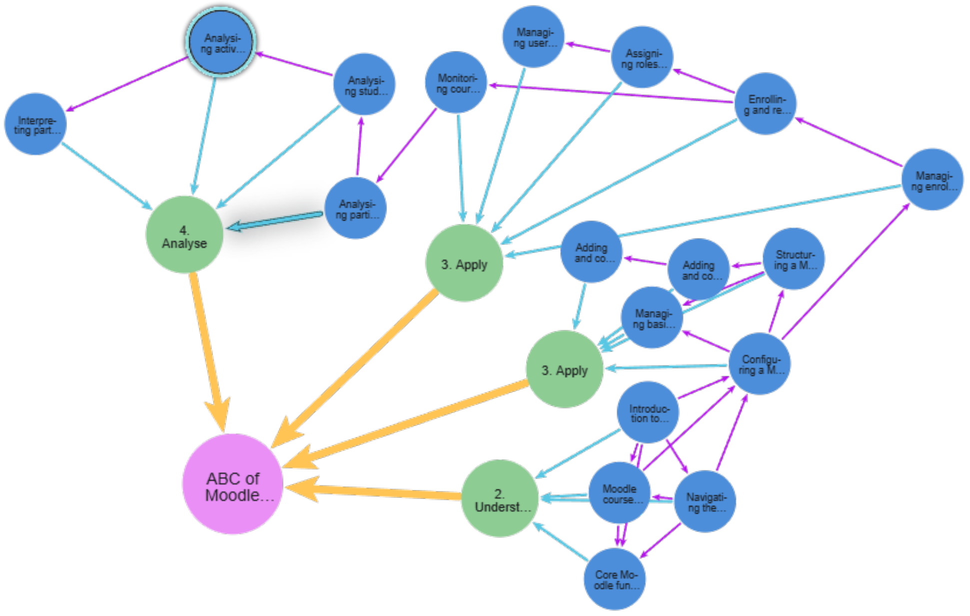

Figure 6.1: Graph-based representation of the course designed with the SPIRAL framework.

6.3 Graph-based Structural Analysis of the Course

To evaluate the structural properties of the designed course, a set of graph-based analyses was conducted on the Learning Unit dependency graph. The analysis focuses exclusively on design-time relations represented by `UNLOCKS` edges, in order to assess the intended pedagogical structure independently of exploratory or hypothesised semantic connections.

Entry Points and Terminal Learning Units. The analysis reveals the presence of a single global entry point in the course graph, corresponding to the introductory learning unit *Introduction to Moodle and its role as an LMS*. This unit exhibits zero in-degree and represents the mandatory starting point for all learning paths, reflecting a strongly guided initial phase that is coherent with the introductory nature of the course and supports learners with limited prior experience.

At the opposite end of the graph, multiple terminal learning units are identified, characterised by zero out-degree. These units correspond to advanced or consolidating topics, such as the interpretation of participation data and the configuration of specific course components. As reported in Table 6.1, the coexistence of a single entry point (in-degree = 0) and multiple terminal units (out-degree = 0) indicates that, while the initial trajectory is tightly controlled, the course allows for diversified completion paths.

Fundamental and Enabling Learning Units. Learning Units with high out-degree values play a fundamental enabling role within the course structure, as they unlock access to multiple subsequent units. These units typically correspond to core operational competencies, such as course configuration and structural organization, and act as foundational components for the rest of the course.

Table 6.2: Degree-based characterization of Learning Units

Role	**Criterion**	**# LUs**
Entry unit	In-degree = 0	1
Terminal units	Out-degree = 0	5
Enabling units	Out-degree ≥ 2	3
Intermediate units	Otherwise	6

As summarised in Table 6.2, three learning units exhibit an out-degree greater than or equal to two, identifying them as enabling units that unlock access to multiple subsequent learning units. Conversely, five learning units present zero out-degree and function as terminal units, marking possible completion points of the learning path. The remaining learning units occupy intermediate positions in the graph, characterised by a limited number of incoming and outgoing prerequisite relations.

Central Learning Units and Structural Bottlenecks. Betweenness centrality analysis identifies a limited number of learning units acting as structural bottlenecks within the course graph. These units lie on a large proportion of shortest paths connecting other learning units and therefore function as key transitional stages in the learning path. As reported in Table 6.3, only four learning units exhibit markedly high betweenness values, ranging from 24 to 39, indicating a concentrated but non-dominant form of structural centrality.

The learning units with the highest betweenness scores correspond to core operational competencies, including course configuration, enrolment management, and monitoring of course participants. Their central position reflects a pedagogically meaningful progression from setup and management tasks toward more advanced, data-driven analysis activities, and not an arbitrary structural constraint.

Table 6.3: Learning Units with highest betweenness centrality values.

Learning Unit	**Betweenness**
Configuring a Moodle course	39
Enrolling and removing users	35
Managing enrolment methods	32
Monitoring course participants	24

Figure 6.2 provides a visual representation of the prerequisite structure among learning units, making explicit the role of these central units in connecting different phases of the course. While the graph does not exhibit a single dominant bottleneck, the presence of a small set of structurally central learning units confirms that the learning path is guided but not fragile, as progression does not depend on a single critical unit.

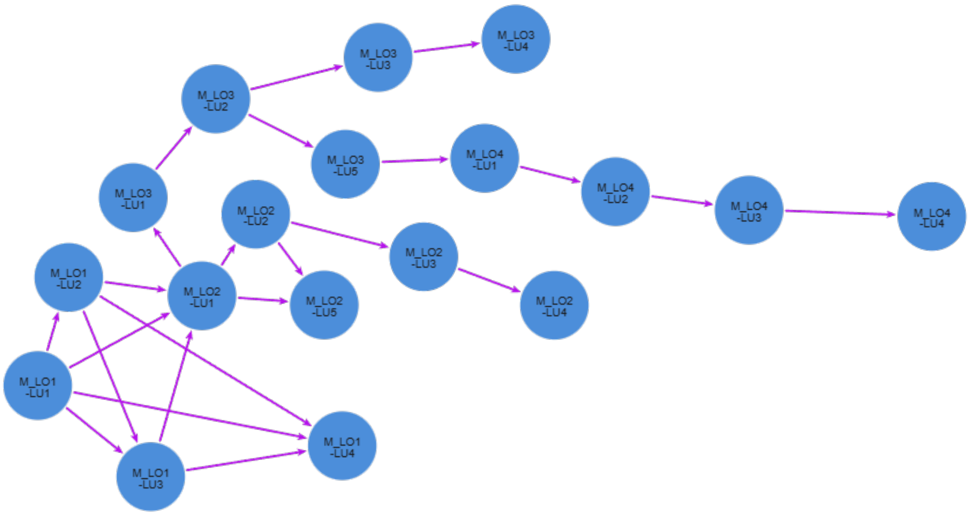

Figure 6.2: Learning Unit dependency graph restricted to `UNLOCKS` relations. The visualization highlights the overall prerequisite structure and the relative centrality of learning units acting as transitional stages within the learning path.

Depth and Progression of learning Paths. The depth of each learning unit was computed as the maximum distance from the global entry point in the `UNLOCKS` graph. The resulting depth distribution reveals a gradual and well-balanced progression across the course, with learning units distributed over multiple levels and a maximum path length of ten prerequisite steps. This finding serves to substantiate the hypothesis that the course under scrutiny fosters a profound and cohesive learning trajectory, distinguished by a sequential accumulation of competencies that eschews both superficial and fractured structures.

Semantic Proximity and Alternative Learning Paths. Semantic similarity relations between learning units were analysed to identify potential alternative learning paths and conceptual overlaps. Most learning units are connected by one or more `Similar_To` relations, reflecting thematic coherence within macro learning outcomes. These relations are predominantly local and typically connect learning units located at comparable depth levels, thereby providing limited flexibility without disrupting the global prerequisite structure.

Critical Interpretation of Equivalence Relations. The analysis identifies only a single `Equivalent_To` relation between two Learning Units. A closer qualitative inspection of this pair reveals that, despite the high semantic similarity detected by the algorithm and the alignment in Bloom level, the two units are not fully interchangeable from a pedagogical perspective. While they address closely related aspects of Moodle course design, they emphasize different operational contexts and instructional intentions.

This result highlights the interpretative role of the instructor within the SPIRAL framework. In this case, the detected equivalence does not correspond to a meaningful didactic redundancy, but rather to a partial overlap in terminology and functional scope. Consequently, the `Equivalent_To` relation can be safely removed without affecting the coherence of the course structure. This outcome should not be interpreted as a limitation; instead, it illustrates the intended human-in-the-loop use of equivalence relations, which are conceived as hypotheses that support reflective analysis without imposing rigid design constraints.

Synthesis. Overall, the combined analysis of degree distribution, betweenness centrality, depth, and semantic similarity depicts a course structure that is robust, interpretable, and pedagogically coherent. The presence of clearly identifiable entry points, fundamental enabling units, central bottlenecks, and terminal learning units supports a guided yet flexible learning experience.

These results highlight the potential of the SPIRAL framework to support transparent and analyzable course design by means of graph-based representations and analytics. In the following section, this potential is further explored through the application of the proposed model, relations, and graph-based metrics to a set of existing courses. This analysis aims to investigate how graph-based representations of learning paths can be used to identify meaningful indicators for evaluating course design, and how such indicators vary across different levels of granularity and abstraction.

Chapter 7

Model Application and Evaluation

7.1 Application on Start-Courses

7.1.1 The Start@UniTo Project

The *Start@UniTo* project was developed at the University of Turin as an open digital education initiative aimed at supporting the transition from secondary school to university and fostering student success in the early stages of higher education. The project provides a collection of online university-level courses offered in an open-access format, designed to be freely accessible without temporal constraints or formal enrolment requirements.

Start@UniTo hosts complete courses, primarily focused on foundational first-year subjects, and is addressed to a heterogeneous audience that includes upper secondary school students in orientation phases, university students, working students, and learners seeking targeted revision or reinforcement of specific disciplinary topics. In this respect, the project is situated within the broader context of open and flexible learning environments, with particular attention to accessibility and reuse of educational resources [58, 57].

From a pedagogical and technological perspective, Start@UniTo integrates adaptive learning approaches and automatic formative assessment mechanisms, with the aim of supporting self-regulated learning through immediate and automated feedback. Previous studies on the project have highlighted the role of automatic assessment and feedback in sustaining learner engagement and facilitating self-evaluation processes, especially in large-scale and open online learning contexts.

A distinctive feature of the Start@UniTo model lies in the internal organization of course contents. Courses are not conceived as strictly linear sequences of activities, but rather as structured collections of *autonomous learning objects*[11]. These learning objects exhibit a variable degree of granularity, ranging from relatively concise and focused resources to more articulated units including extended explanations, interactive activities, and self-assessment components. Importantly, such objects are not characterized by consistently well-defined boundaries, nor are they designed according to a uniform instructional template; similarly, learning outcomes are not systematically made explicit at the level of individual objects[59].

Despite this heterogeneity, the overall design of the project and the observed patterns of use suggest forms of engagement that are not rigidly constrained by linear progression or by the requirement of completing an entire course. Learners may selectively access and combine learning objects according to their individual needs, prior knowledge, and learning goals, resulting in flexible and non-uniform modes of course utilization.

Overall, Start@UniTo can be interpreted not merely as a platform for the delivery of online courses, but as a learning support environment that enables relatively open and modular forms of use, albeit in an implicit and non-formalized manner. In this sense, the project constitutes a relevant application context for the analysis of relationships between content structure, modes of use, and participation-related indicators. Instead of representing a deliberately implemented modular learning model, Start@UniTo offers a real-world educational ecosystem in which such characteristics emerge organically, providing a meaningful empirical basis for exploratory analyses of flexible learning scenarios at university level.

7.1.2 Data Preparation/Extraction and Workflow

The analytical setup adopted for the application to the Start-Courses dataset was designed to enable an exploratory investigation of structural properties of courses in a context that was not originally conceived according to the SPIRAL model. As a consequence, a number of methodological assumptions and adaptations were required, which are explicitly described in the following.

A subset of fifteen courses was selected from the Start@unito platform. The selection was performed randomly among the different thematic areas available on the platform, with the aim of obtaining a heterogeneous sample in terms of disciplinary domains, while preserving the exploratory nature of the analysis.

It is important to note that the selected courses were not designed according to the SPIRAL framework. In particular, neither macro nor micro learning outcomes are explicitly defined within the courses, and no outcome-based instructional design is formally available. In order to enable the proposed structural analysis, an operational representation of the internal organization of the courses therefore had to be constructed. To this end, a reverse-engineering process was adopted, aimed at extracting the available information and augmenting it as necessary in order to derive a model suitable for the intended structural analysis.

As a first step, Moodle course sections were used as an initial aggregation level for identifying learning units. In cases where a single section included multiple assessment activities, and in particular multiple tests, the section was further subdivided into multiple learning units, each associated with a single test. This choice was motivated by the central role played by assessment activities in the Start@UniTo courses and by the availability of structured and analysable information at test level.

Since learning outcomes are not explicitly defined in the courses, an additional step was required to associate a learning outcome with each identified learning unit. This process was carried out using an AI-assisted approach based on Microsoft Copilot, guided by a set of predefined rules. In particular, the association procedure focused on the analysis of the types of questions included in each test. Based on the cognitive demands implied by the questions, Copilot was instructed to identify the maximum level of Bloom's taxonomy required to successfully answer the test and to generate a corresponding learning outcome formulated at that cognitive level.

To support this process, examples of assessment questions corresponding to different levels of Bloom's taxonomy were provided to the system, up to level 5 (*Evaluate*). Higher cognitive level were not considered, as no assessment activities requiring higher-level cognitive processes were identified in the selected courses. This procedure resulted in a set of inferred learning outcomes, one for each learning unit, which were subsequently used for graph construction and analysis.

Participation data were extracted for each course up to December 31, 2025. These data include the number of enrolled users and the number of users who completed the course and obtained the final certificate. The extracted information was used to compute course-level completion rates.

The resulting course representations were then implemented in a Neo4j graph database. For each course graph, three structural metrics were computed: average degree, average betweenness centrality, and average clustering coefficient. Finally, an exploratory correlation analysis was conducted to investigate the existence of potential associations between these structural metrics and course completion rates.

7.1.3 Graph Analysis of Start@UniTo Courses

Descriptive Analysis of the Graph

The graph constructed from the UniTo-START catalogue comprises a total of 596 nodes and 1097 relationships. Courses in the catalogue are explicitly articulated into Learning Units, resulting in a multi-layer representation that models course structure, learning units, and learning outcomes. In particular, the graph includes 238 Learning Unit nodes, corresponding to instructional units identified from the platform structure, which are linked to 238 Learning Outcomes and course sections through dedicated structural relationships.

The inferred semantic and cognitive relationships are restricted to the intra-course context, as the graph represents a snapshot of the START catalogue aimed at analysing the internal structural and semantic properties of individual courses. Consequently, all relationships between Learning Outcomes and between Learning Units should be interpreted as local characteristics of course design and internal organisation.

Restricting the analysis to Learning Outcome–Learning Outcome relations, the graph includes a total of 258 LO–LO edges, distributed as follows: 135 `Similar_To` relations, 116 `Connected_To` relations, 5 `Equivalent_To` relations (counted as reciprocal pairs), and 2 `Possible_Prerequisite_Of` relations. This distribution highlights the predominance of semantic similarity and weak cognitive connection relations, while equivalence relations and explicit prerequisite hypotheses are comparatively rare.

At the Learning Unit level, the inferred relations mirror the structure observed at the Learning Outcome level, yielding 258 LU–LU relations with the same distribution: 135 `Similar_To`, 116 `Connected_To`, 5 `Equivalent_To`, and 2 `Probably_Unlocks`. The `Probably_Unlocks` relation represents a directional dependency between Learning Units derived from the inferred cognitive directionality between their associated Learning Outcomes.

In addition to inferred relations, the graph is characterised by a set of structural relationships used to represent course organisation and the alignment between learning units and learning outcomes. Specifically, 238 `HAS_OUTCOME` relationships link Learning Units to their associated Learning Outcomes, while 238 `IS_PART_OF` relationships model the inclusion of Learning Outcomes within course structures. Furthermore, 105 `IS_SECTION_OF` relationships represent the decomposition of courses into 105 sections. Taken together, these relationships define the structural backbone of the graph and enable an explicit representation of the hierarchical and organisational aspects of courses.

From a cognitive perspective, the Learning Outcomes in the dataset exhibit a non-uniform distribution across Bloom's taxonomy levels. The classification available for this snapshot of the catalogue[1] covers levels 1 to 4, with 40 Learning Outcomes at level 1 (Remember), 17 at level 2 (Understand), 92 at level 3 (Apply), and 89 at level 4 (Analyse). The distribution is shown in Figure 7.1.

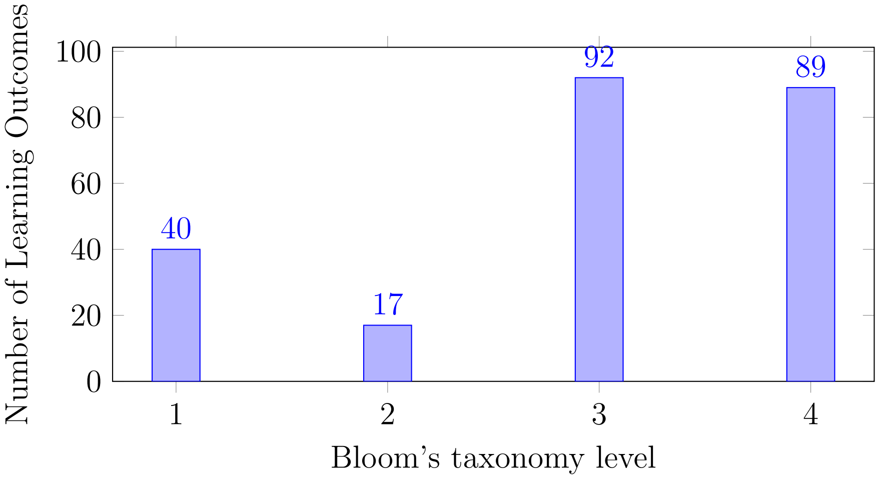

Figure 7.1: Distribution of Learning Outcomes across Bloom's taxonomy levels in the UniTo-START catalogue

A visual overview of the graph structure is provided in Figure 7.2. The visualisation highlights the modular organisation of courses into sections and Learning Units, together with local connectivity patterns induced by `Similar_To` and `Connected_To` relations. Since inferred relationships are limited to the intra-course context, the resulting topology reflects the internal structure and design choices of individual courses.

Degree Distribution

To further characterise the internal structure of courses in the UniTo-START catalogue, we analyse the distribution of the *intra-course degree* of Learning Outcomes. For each Learning Outcome, the intra-degree is defined as the number of semantic or cognitive relations linking it to other Learning Outcomes within the same course.

Across the dataset, the average intra-course degree is 2.17, with a median value of 1.0. The minimum observed intra-degree is 0, while the maximum

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[1] The analysis presented is based on a subset of 15 courses randomly selected from the more than 80 courses currently available on the Start@UniTo platform.

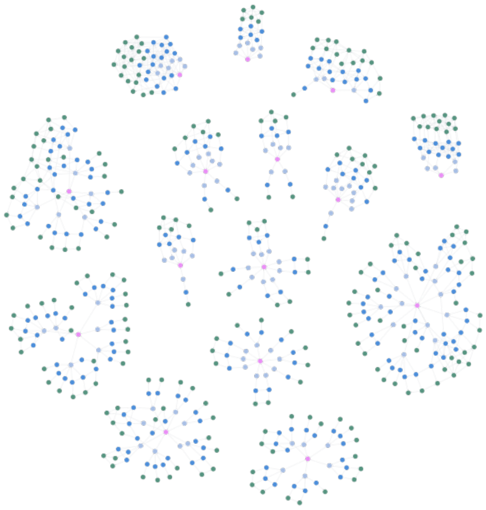

Figure 7.2: Visual representation of the UniTo-START graph.

reaches 13. This range points to a markedly heterogeneous internal connectivity: while some Learning Outcomes act as local hubs within a course, others appear weakly connected or entirely disconnected from the inferred semantic structure.

A particularly relevant result concerns the presence of a substantial number of Learning Outcomes with zero intra-course degree. In total, 72 Learning Outcomes do not exhibit any inferred semantic or cognitive relation with other outcomes within their own course. These Learning Outcomes can be described as *intra-course isolated*, meaning that, under the adopted thresholds and modelling assumptions, they do not participate in the internal semantic network of the course.

The existence of a high number of isolated Learning Outcomes admits two complementary interpretations. On the one hand, it may indicate a form of *internal fragmentation*, where certain learning objectives are weakly integrated into the overall course design and lack explicit semantic or cognitive links to other outcomes. On the other hand, these isolated nodes may correspond to *conceptual boundary Learning Outcomes*, representing highly specific, transversal, or marginal objectives that do not naturally activate strong semantic relations with the rest of the course content.

The overall distribution of intra-course degree values is shown in Figure 7.3. The histogram reveals a strongly right-skewed distribution: most

Learning Outcomes exhibit low intra-degree values (0–2), while a limited number of nodes concentrate significantly higher degrees. This discrepancy between mean and median further confirms that intra-course semantic connectivity is unevenly distributed, with a small subset of Learning Outcomes playing a structurally central role and a majority occupying peripheral positions within the course-level semantic network.

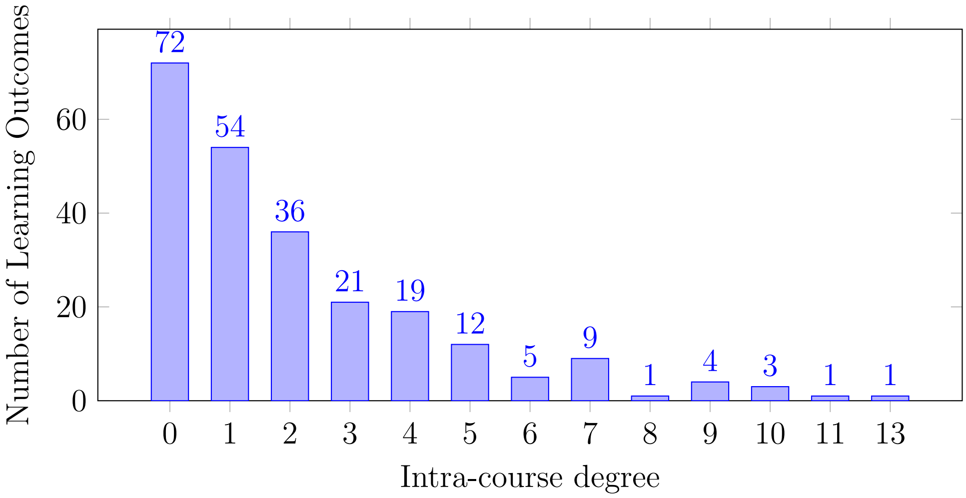

Figure 7.3: Distribution of intra-course degree values for Learning Outcomes in the UniTo-START catalogue.

Betweenness Centrality

To complement the analysis of internal connectivity, we now examine the *betweenness centrality* of Learning Outcomes in the UniTo-START catalogue. Betweenness centrality measures the extent to which a node lies on the shortest paths between other pairs of nodes, and thus identifies Learning Outcomes that act as structural mediators within the intra-course semantic network.

In this analysis, betweenness is computed exclusively on intra-course relations. As a result, high betweenness values do not simply reflect highly connected Learning Outcomes, but rather outcomes that connect distinct subsets of objectives within the same course.

The results show that betweenness is strongly concentrated on a limited number of Learning Outcomes. Table 7.1 reports the ten Learning Outcomes with the highest betweenness values, together with their intra-course degree. These Learning Outcomes function as *conceptual hubs*, supporting connectivity between different parts of the course and contributing to the overall coherence of the instructional structure.

Table 7.1: Top Learning Outcomes by betweenness centrality in the UniTo-START catalogue (intra-course LO–LO graph).

#	Learning Outcome	Degree	Betweenness
1	Understand the general structure and chemical functions of nerve agents.	6	65.0
2	Understand the regulatory classification of explosives and the main triggering devices.	5	59.0
3	Understand the genetic code and translation mechanisms.	9	47.83
4	Understand the fundamental principles of international conventions on chemical and biological weapons.	4	45.0
5	Understand the distinction between deflagration and detonation in terms of speed and mechanism.	2	32.0
6	Understand the historical context and basic features of nuclear weapons.	2	32.0
7	Understand the fundamental features of political, imperial, and colonial systems in the contemporary age.	9	29.21
8	Understand the nature and role of biological toxins.	5	28.0
9	Analyze elementary functions through domain, graph, and properties.	5	26.0
10	Analyze chronological and thematic relationships among conflicts, reforms, and global transformations.	10	24.37

Notably, high betweenness does not necessarily coincide with high degree. Some Learning Outcomes exhibit a moderate number of direct connections while still occupying a central position in the network of shortest paths. This confirms that betweenness captures a complementary structural dimension with respect to degree, distinguishing between Learning Outcomes that are simply well connected and those that are strategically positioned for maintaining course-level cohesion.

From an instructional design perspective, Learning Outcomes with high betweenness can be interpreted as conceptually critical points within the course. Their formulation, positioning, and clarity are particularly important, as weaknesses at these nodes may disproportionately affect the continuity and comprehensibility of the learning pathway.

Weighted Shortest Paths

To further investigate the internal organisation of courses in the UniTo-START catalogue, we analyse the distribution of weighted shortest path distances between Learning Outcomes within the intra-course semantic network. Shortest path distance captures the minimum semantic or cognitive separation between pairs of Learning Outcomes and provides insight into the navigability and structural cohesion of individual courses. In this analysis, shortest paths are computed on intra-course Learning Outcome graphs using semantic distance as edge weight, defined as $d = 1 - \mathrm{sem}_{\mathrm{sim}}$.

In the analysed dataset, the average shortest path distance is equal to 0.67, with a median value of 0.49. The 90th percentile of the distance distribution is 1.35, while the maximum observed distance reaches 2.86. Overall, these values indicate that, when a connection exists, most Learning Outcomes are separated by a very limited number of semantic steps.

The low average and median distances suggest that intra-course semantic networks are generally *compact*. In most cases, Learning Outcomes are either directly connected or reachable through one or two intermediate objectives. Even when considering the upper tail of the distribution, the fact that 90% of shortest paths remain below 1.35 highlights the absence of long semantic chains within courses.

The maximum distance of approximately 2.86 points to the presence of a small number of Learning Outcome pairs that are more distant from each other, typically associated with objectives belonging to different conceptual areas of the same course or positioned in structurally distant sections. However, these cases remain marginal and do not significantly affect the overall compactness of the network.

From a structural perspective, this configuration suggests that, once isolated Learning Outcomes are excluded, the internal semantic space of courses is characterised by *short paths and high reachability.* This property is consistent with an instructional organisation in which conceptual transitions between objectives require limited cognitive jumps and in which centrally positioned Learning Outcomes effectively connect different parts of the course.

Taken together, the analyses of intra-course degree, betweenness centrality, and shortest path distances provide a structural characterisation of the

Learning Outcome network at the course level, highlighting differences in conceptual roles and levels of integration among objectives. These indicators form the basis for exploring how specific structural configurations may be associated with patterns of course engagement and completion, which are examined in the following section.

7.1.4 Link between Graph Metrics and Completation Rate

The results are reported at course level by relating participation indicators to the structural metrics computed on the course graphs. In particular, course completion rate was considered as the dependent variable, while average degree, average betweenness centrality, and average clustering coefficient were analyzed as structural explanatory variables.

As a first step, an exploratory analysis was conducted using scatter plots to visually inspect the relationships between completion rate and each structural metric (see Figure 7.4). The resulting distributions show a high variability in completion rates across the selected courses and do not reveal clear linear relationships for all metrics. In particular, the relationship with average betweenness appears to be more pronounced than those observed for average degree and average clustering. This finding suggests the presence of a monotonic rather than strictly linear association.

Subsequently, Pearson and Spearman correlation coefficients were computed to quantify the associations between completion rate and the considered structural metrics. The results indicate that average degree exhibits very weak correlations with completion rate, both in terms of linear and monotonic association. Similarly, average clustering coefficient shows associations of limited magnitude. By contrast, average betweenness centrality presents a moderate negative Spearman correlation, indicating that higher values of intermediary centrality are, on average, associated with lower completion rates.

In order to account for the effect of course size, measured through the number of learning units, partial correlations were computed by controlling for this variable. Under this condition, the association between average betweenness and completion rate is substantially reduced, whereas the correlations associated with average degree and average clustering show more limited variations. This suggests that a significant portion of the observed association between betweenness and completion rate may be attributable to scale effects related to course size.

An additional analysis was performed using normalized versions of the

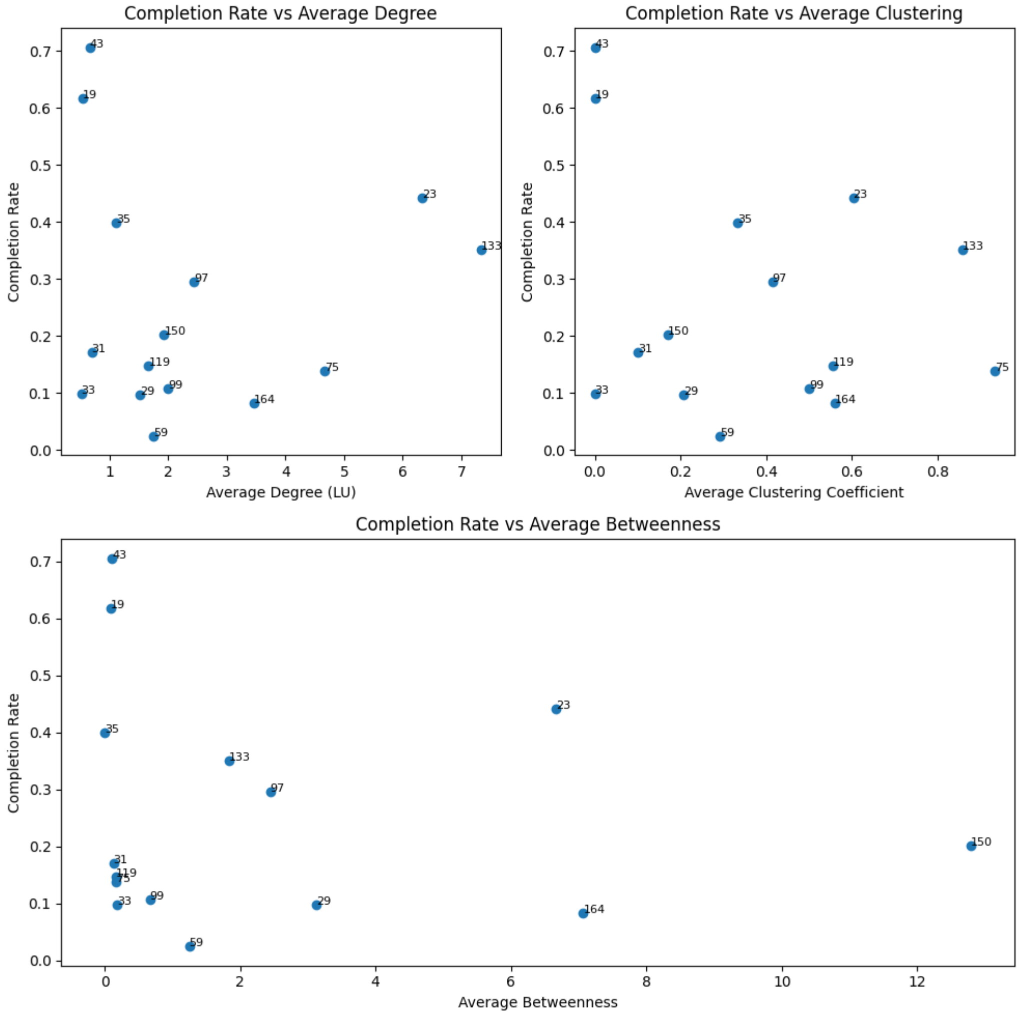

Figure 7.4: Scatter plots showing the relationship between course completion rate and selected structural metrics computed on course graphs: average degree (top left), average clustering coefficient (top right), and average betweenness centrality (bottom). Each point represents a course.

structural metrics, obtained by dividing each metric by the number of learning units in the course. In this case as well, normalized betweenness and normalized clustering exhibit moderate negative correlations with completion rate, while normalized average degree shows a weaker association.

The observed results suggest that the considered structural metrics do not contribute uniformly to explaining differences in course completion levels. In particular, the weak associations identified for average degree indicate that the mean number of connections among learning units, when considered in isolation, does not appear to be a decisive factor with respect to completion rate. Similarly, average clustering coefficient exhibits associations of limited magnitude, suggesting that the presence of locally dense substructures is not, by itself, sufficient to account for the observed variability across courses.

Average betweenness centrality, by contrast, displays a more differentiated behavior. The negative association observed in the uncontrolled analyses suggests that higher levels of intermediary centrality within the course structure may be associated with lower completion rates. However, the substantial reduction of this association once course size is controlled for indicates that this relationship is at least partly influenced by scale effects related to the number of learning units and the overall structural complexity of the course.

The analysis of normalized metrics and partial correlations further shows that certain local structural properties, when considered at comparable course sizes, maintain more stable associations with completion rate than global structural indicators. This suggests that the local configuration of relationships among learning units may play a more relevant role than global centralization alone in shaping observed participation outcomes.

Overall, these preliminary observations indicate that the relationships between course structure and participation behaviors are articulated and cannot be reduced to a single structural indicator. They provide a basis for a more in-depth interpretation of the results, which will be developed in the subsequent chapter, taking into account the characteristics of the application context and the observed modes of course utilization.

7.2 Application on EDVANCE Catalogue

7.2.1 The EDVANCE Project

The EDVANCE project represents one of the *Digital Education Hub* for higher education in Italy specifically aimed at the development of advanced digital competences. Coordinated by the Politecnico di Milano and funded by the European Union within the framework of the *Piano Nazionale di Ripresa e Resilienza* (PNRR), EDVANCE involves a network of 17 Italian universities (UniTO for instance) and AFAM institutions (*Alta Formazione Artistica, Musicale e Coreutica*). The project aims to strengthen and innovate higher education offerings through digitally enhanced, high-quality, and transdisciplinary learning opportunities.

At the core of the project is the development of a federated online portal providing access to a large catalogue of free online educational pathways, including Massive Open Online Courses (MOOCs) and microcredentials. These learning opportunities are designed to address the growing demand for digital and transversal skills and cover thematic areas such as data literacy, artificial intelligence, digital sustainability, and emerging challenges of the contemporary digital society.

The courses offered within the EDVANCE catalogue are delivered by partner institutions and target a broad audience, including university students, professionals, educators, and citizens interested in upskilling or reskilling in digital domains. Upon successful completion of the learning activities, participants are awarded microcredentials and open badges, which serve as digitally verifiable certifications of the acquired competences and can be leveraged in both academic and professional contexts. These microcredentials are also shared within the UNITA – Universitas Montium European University Alliance, further strengthening the connection between the EDVANCE educational ecosystem and the broader UNITA institutional and pedagogical framework, as well as reinforcing the relevance of the present research within that context.

In addition to learner-oriented educational pathways, EDVANCE also includes initiatives dedicated to the professional development of academic staff and institutional personnel. These activities aim to foster the adoption of innovative teaching methodologies and to support the overall quality and sustainability of digitally enhanced higher education.

Owing to the size of the consortium, the heterogeneity of the offered courses, and the explicit focus on modular and flexible learning pathways, the EDVANCE project constitutes a particularly relevant context for investigating computational approaches to the analysis, comparison, and organization of microcredentials within a unified educational ecosystem.

7.2.2 The UniTo Microcredential Catalogue and Methodological Workflow

The application of the model and analytical techniques proposed in this work focuses on a specific subset of the EDVANCE initiative, namely the catalogue of microcredentials delivered by the University of Turin (UniTo). The analysis is further restricted to those courses for which a complete instructional design sheet is available, which is used as the primary source for the extraction and formalization of Learning Outcomes[2].

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[2] The most recent instructional design sheets considered in this study were collected on 30/12/2025.

It is important to note that the EDVANCE project was launched prior to the completion and consolidation of the SPIRAL model. As a consequence, instructors involved in course design were not provided with the structured design framework illustrated in the application described in Chapter 6. In particular, the adopted design approach does not include an explicit multi-level articulation of Learning Outcomes, nor the definition of Learning Units as autonomous instructional entities.

The instructional design of the EDVANCE courses considered in this study can therefore be characterized as a form of *macro-design*, in which each course is described exclusively through a set of course-level Learning Outcomes. Within this context, all Learning Outcomes are treated as *macro Learning Outcomes*, without internal decomposition into micro-level objectives or associated Learning Units.

This structural simplification directly affects the representation model adopted for the analysis. Compared to a course fully designed according to the SPIRAL model, the resulting graph includes a reduced set of node and relationship types. In the UniTo–EDVANCE context, the graph representation comprises only courses and Learning Outcomes, connected through a limited set of relations defined either between courses and Learning Outcomes or between pairs of Learning Outcomes. Specifically, the following relationship types are considered:

- ▷ `IS_MACRO_OUTCOME_OF`, linking each Learning Outcome to its associated course;
- ▷ `Connected_To`, representing a weak, directed relation between Learning Outcomes across different cognitive levels;
- ▷ `Similar_To`, indicating a significant semantic similarity between Learning Outcomes at the same cognitive level;
- ▷ `Equivalent_To`, identifying semantically interchangeable Learning Outcomes;
- ▷ `Possible_Prerequisite_Of`, denoting a candidate prerequisite relation subject to instructor validation.

All these relations are not specified at design time, but are entirely inferred through computational analysis according to the rules described in Section 5.2.2, based on the semantic similarity of Learning Outcome texts and their cognitive characterization through Bloom's taxonomy.

Under these assumptions, the UniTo-EDVANCE catalogue can be interpreted as a *semantic graph of Learning Outcomes*, in which each course is represented as a collection of educational objectives and infered relations between Learning Outcomes make explicit patterns of semantic affinity, cognitive continuity, and potential conceptual progression. In the absence of a multi-level instructional structure based on Learning Units, these relations do not encode prescribed learning sequences, but rather render observable the latent network of connections spanning the course catalogue.

From Instructional Design Sheets to a Structured Dataset. The analytical workflow begins with the instructional design sheets available for the selected UniTo microcredentials within the EDVANCE catalogue. For each course, the design sheet provides the course title and a list of course-level Learning Outcomes. These contents were consolidated into a structured comma-separated values (CSV) file to ensure consistency across courses and to enable computational processing. Each row of the resulting dataset corresponds to a single Learning Outcome and includes: (i) the UniTo course name (English), (ii) the course category, and (iii) the Learning Outcome text.

Bloom Level Assignment. To incorporate a cognitive characterization of Learning Outcomes, each Learning Outcome was automatically assigned to a Bloom category and an associated ordinal Bloom level. This step relies on the classifier described in Section 5.1.1, which takes as input the Learning Outcome text and outputs a predicted Bloom category together with its corresponding level. In the present UniTo–EDVANCE dataset, all Learning Outcomes are treated as macro Learning Outcomes (course-level outcomes). The predicted Bloom level is subsequently used as the cognitive component in the computation of directed relations between Learning Outcomes, consistently with the representation rules described in Section 5.2.2.

Data Representation and Import into Neo4j. The CSV dataset was loaded into Python as a dataframe, where each Learning Outcome was assigned a unique identifier corresponding to its row index. The graph database was instantiated in Neo4j through a Python-based import procedure. Two node types were created: `Course` and `LearningOutcome`. Course nodes are uniquely identified by the English course name (`name_en`). Learning Outcome nodes store, as properties, the unique identifier (`id`), the Learning Outcome text, the predicted Bloom category, and the predicted Bloom level, together with a `lo_type` property indicating that all outcomes in this dataset are macro-level outcomes. Each Learning Outcome node is linked to its course through the relation `IS_MACRO_OUTCOME_OF`.

Since the EDVANCE course design sheets do not include design-time prerequisite structures or Learning Units, all relations between Learning Outcomes were inferred computationally. For each ordered pair of Learning Outcomes (LO_i, LO_j), the workflow computes: (i) a semantic similarity score $\text{sem}_{\text{sim}}(LO_i, LO_j)$, obtained from sentence-embedding cosine similarity after a lightweight text normalization step, and (ii) the Bloom-level difference $\Delta_B = B(LO_j) - B(LO_i)$. Relations are introduced according to the thresholds and decision rules defined in Section 5.2.2. Each inferred relation stores the semantic similarity value as a weight property (`weight`), and a boolean flag (`intra_course`) indicating whether the connected Learning Outcomes belong to the same course or to different courses.

Graph Analysis. Once the graph was instantiated, the UniTo-EDVANCE catalogue was analysed using Cypher queries and, where appropriate, Neo4j Graph Data Science procedures. The analysis focuses on structural properties (such as node and edge counts, connectivity, and component structure), centrality measures at both Learning Outcome and course levels, and path-based measures, including weighted shortest paths computed on the induced semantic relations. The results of these analyses are presented in Section 7.2.3 and discussed with reference to the interpretation of the catalogue as a semantic design space insteaf of a prescriptive set of learning sequences.

7.2.3 Graph Analysis of the UniTo Catalogue

In line with the methodological perspective outlined in Section 5.2, the graph-based metrics discussed in this analysis are not intended to drive automatic pedagogical decisions. Rather, they are employed as interpretative tools aimed at supporting a structured reading of the catalogue's pedagogical and semantic organization. Indicators such as degree distribution, connectivity patterns, and component structure make explicit latent structural properties of the Learning Outcome network, which require contextual and instructional interpretation by domain experts. From this perspective, the computational model exposes relational patterns, while their educational meaning remains grounded in human judgement.

Descriptive Analysis of the Graph

The graph constructed from the UniTo-EDVANCE catalogue comprises a total of 372 nodes and 1460 relationships. Nodes are divided into 39 Course nodes and 333 Learning Outcome nodes, reflecting the modelling choice to represent each course as a collection of macro-level learning objectives, without an explicit articulation into Learning Units or micro Learning Outcomes.

Each Learning Outcome is associated with exactly one course through the `IS_MACRO_OUTCOME_OF` relationship, which appears 333 times, once for each Learning Outcome. All remaining relationships in the graph connect pairs of Learning Outcomes and are entirely inferred through the computational analysis described in the representation model.

Restricting the analysis to Learning Outcome–Learning Outcome relations, the graph includes 1127 LO–LO edges, distributed as follows: 880 `Connected_To` relations, 225 `Similar_To` relations, 13 `Equivalent_To` relations (counted as pairs with `Equivalent_To`), and 9 `Possible_Prerequisite_Of` relations. This distribution shows that most connections between Learning Outcomes take the form of weak, directed relations (`Connected_To`), while stronger semantic affinities and equivalences occur less frequently.

Learning Outcome relations are further characterised by the `intra_course` property, which distinguishes connections internal to a single course from those spanning different courses. Overall, 447 LO–LO relations are intra-course, while 680 relations connect Learning Outcomes belonging to different courses. More specifically, `Connected_To` relations account for 357 intra-course and 523 cross-course edges; `Similar_To` relations for 79 intra-course and 146 cross-course edges; `Equivalent_To` relations for 5 intra-course and 8 cross-course edges; and `Possible_Prerequisite_Of` relations for 6 intra-course and 3 cross-course edges.

From the perspective of local density, the average number of LO–LO relations per Learning Outcome is 3.38, indicating that each learning objective is connected, on average, to approximately four other Learning Outcomes through semantic or cognitive relations. When considering only cross-course relations (`intra_course = false`), the average number of relations per Learning Outcome decreases to 2.04, based on the 761 cross-course edges. This result highlights that a substantial portion of the semantic connectivity is not confined within individual courses but extends across the catalogue, suggesting the presence of a network of conceptual affinities linking different microcredentials.

From a cognitive perspective, the Learning Outcomes in the UniTo-EDVANCE catalogue exhibit a structured distribution across Bloom's taxonomy levels. Following the standard six-level classification (Remember, Understand, Apply, Analyse, Evaluate, Create), 30 Learning Outcomes are classified at level 1 (Remember), 51 at level 2 (Understand), 67 at level 3 (Apply), 80 at level 4 (Analyse), 52 at level 5 (Evaluate), and 53 at level 6 (Create). The distribution (Figure 7.5) shows a concentration in the intermediate cognitive levels, with a peak at Analyse, while higher-order cognitive objectives remain well represented.

A visual overview of the graph structure is provided in Figure 7.6, which

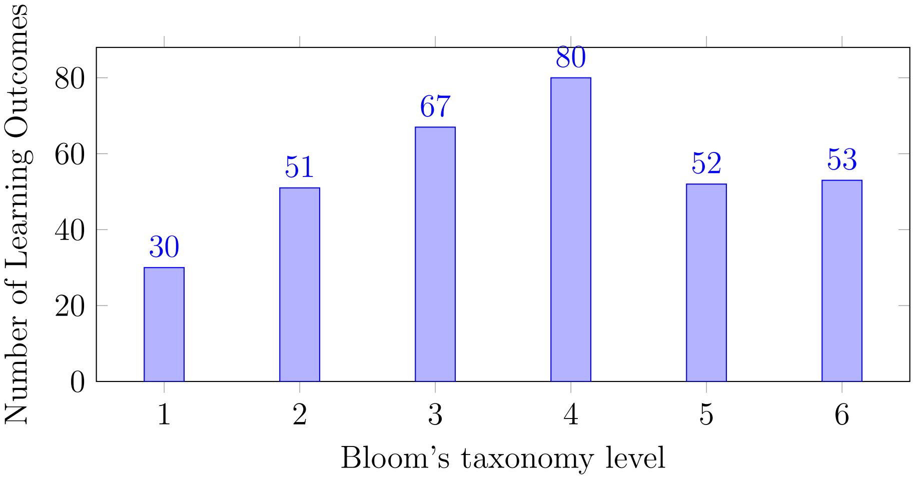

Figure 7.5: Distribution of Learning Outcomes across Bloom's taxonomy levels in the UniTo-EDVANCE catalogue.

makes evident the presence of dense intra-course clusters as well as numerous cross-course connections linking different areas of the catalogue. These cross-course links contribute to the formation of a semantic backbone that spans multiple courses, highlighting the non-fragmented nature of the overall structure.

The figure also reveals the presence of two isolated components, located in the lower part of the visualization and corresponding to the courses *Just and sustainable energy transition: economy and engineering at a crossroad* and *ChatGPT for Coding in Life Sciences*. In both cases, the associated Learning Outcomes do not exhibit any cross-course relations with the rest of the catalogue. This isolation can be interpreted as the result of a strong thematic specificity of the courses, which prevents the activation of semantic links under the adopted thresholds. In the context of online microcredentials, such a configuration may limit the integration of these courses into broader learning pathways, while at the same time providing useful information for monitoring and potentially realigning the catalogue over time from instructional design perspective.

It should be noted that the UniTo-EDVANCE catalogue analysed in this study represents a partial snapshot of the overall microcredential offer. The final catalogue is expected to include more than 80 courses, potentially increasing both the density and the diversity of cross-course semantic connections. For this reason, repeating the present graph-based analysis on future, more complete versions of the catalogue will be particularly relevant to assess the stability of isolated components and to observe how the progressive

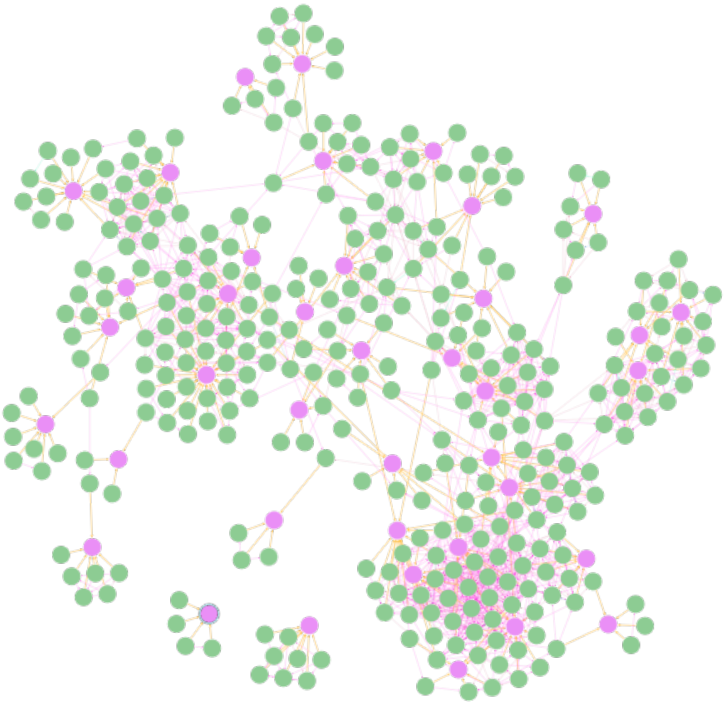

Figure 7.6: Visual representation of the UniTo-EDVANCE Learning Outcome graph.

expansion of the offer influences the global connectivity and integration of learning pathways.

Degree Distribution

Intra-course Degree Distribution Considering exclusively intra-course relations (`intra_course = true`), the analysis of the degree distribution provides insight into the internal connectivity structure of individual courses and supports the assessment of their conceptual coherence.

At catalogue level, the average intra-course degree of Learning Outcomes is equal to 2.68, with a median value of 2, a minimum of 0, and a maximum of 10. This indicates that, within their own course, Learning Outcomes are connected on average to fewer than three other objectives through semantic or cognitive relations. The distribution of degree values is markedly heterogeneous. In particular, 77 Learning Outcomes exhibit an intra-course degree equal to zero, indicating the absence of semantic or cognitive connections with other Learning Outcomes within the same course under the adopted criteria.

Figure 7.7 shows the histogram of the intra-course degree distribution. The distribution is strongly right-skewed: most Learning Outcomes are characterised by low to moderate degree values, predominantly between 1 and 4, while only a limited number of nodes reach higher degree values. A small subset of Learning Outcomes exhibits intra-course degree values greater than or equal to 7, with only two nodes reaching the maximum observed value of 10. This pattern suggests the presence of locally central Learning Outcomes that act as internal conceptual hubs within their respective courses, while the majority of objectives remain weakly connected.

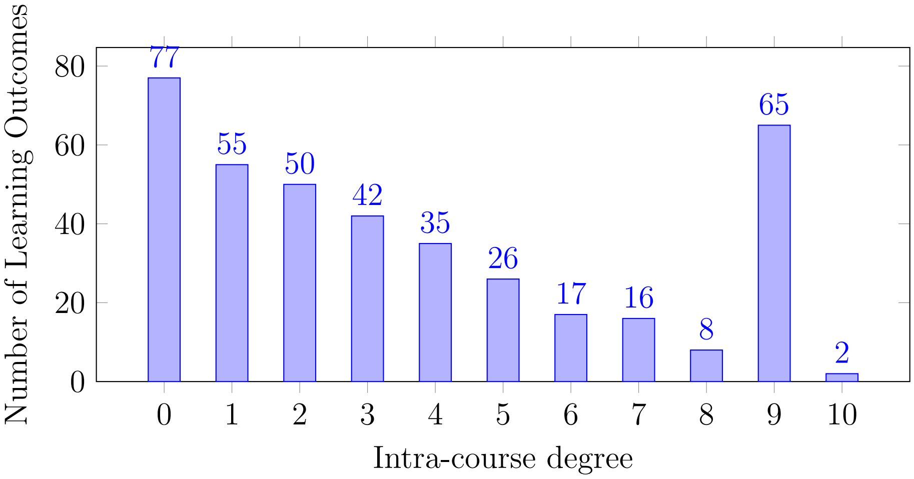

Figure 7.7: Histogram of the intra-course degree distribution of Learning Outcomes in the UniTo-EDVANCE catalogue.

A course-level analysis further reveals substantial variability in internal connectivity profiles. Courses such as *AI and robotics in surgery*, *Basic knowledge of Artificial Intelligence*, and *Advancing Cancer Immunotherapy Through AI Technology* exhibit relatively high average intra-course degree values, indicating dense internal semantic structures and strong integration among their Learning Outcomes. In these courses, the maximum intra-course degree reaches values between 7 and 10, highlighting the presence of particularly central Learning Outcomes that organise the internal conceptual space of the course.

Conversely, several courses display very low average intra-course degree values, in some cases equal to zero. Examples include *ABC – Computational Reproducibility for Life Scientists* and *Crash course on single-cell RNA-seq*, in which none of the Learning Outcomes is semantically connected to other objectives within the same course according to the adopted criteria. While this configuration may reflect the limited size of the courses or the highly specialised nature of their learning objectives, it also points to a low level of internal semantic cohesion, which may warrant further consideration from an instructional design perspective.

Overall, the intra-course degree analysis highlights that the UniTo-EDVANCE catalogue includes courses characterised by markedly different internal connectivity structures, ranging from highly cohesive semantic configurations to nearly disconnected sets of Learning Outcomes. These results emphasise the relevance of intra-course degree as a course-level indicator of semantic organisation and provide a foundation for subsequent analyses focused on cross-course integration and catalogue-level structure. These results suggest that high intra-course degree values are not merely structural properties of the graph, but correspond to meaningful pedagogical relationships within courses. In this sense, intra-course hubs often emerge around Learning Outcomes that play an organising role in the internal conceptual structure of a course, either by aggregating closely related objectives or by mediating cognitively ordered learning progressions.

A closer inspection of the strongest intra-course relations reported in Table 7.2 reveal potential redundancies within individual courses. For instance, in the course *Artificial intelligence applications in Mass Spectrometry Data Analysis*, the presence of two `Equivalent_To` relations between pairs of Learning Outcomes suggests that these objectives are semantically and cognitively overlapping, despite being formulated as distinct outcomes. Within the same course, such equivalences may indicate an unintended duplication of learning objectives. While this does not necessarily represent a flaw, it highlights opportunities for refinement at design time, for example by merging closely aligned outcomes or by clarifying their intended distinctions. From this perspective, the identification of intra-course equivalences can support instructors in reviewing and improving the internal coherence and clarity of course learning objectives.

Table 7.2: List of strong intra-course relations between Learning Outcomes in the UniTo-EDVANCE catalogue.

Course	**Relation between Learning Outcomes**	**Sem. sim.**
AI and robotics in surgery	*Compare traditional and AI-assisted surgical workflows, identifying strengths and limitations of each* $\xrightarrow{\texttt{Possible\_Prerequisite\_Of}}$ *Propose improvements or innovations in current AI-augmented surgical workflows*	0.900
Advancing Cancer Immunotherapy Through AI Technology	*Critically evaluate the potential and limitations of using AI in immunotherapy* $\xrightarrow{\texttt{Possible\_Prerequisite\_Of}}$ *Produce scientific and outreach materials (slides, short reports, infographics) illustrating AI applications in immunotherapy*	0.893
Artificial intelligence applications in Mass Spectrometry Data Analysis	*Know the main Machine Learning models applied to the analysis of mass spectrometry data* $\xrightarrow{\texttt{Equivalent\_To}}$ *Understand the limits of machine learning models for mass spectrometry*	0.900
Artificial intelligence applications in Mass Spectrometry Data Analysis	*Discuss the strengths and criticisms of AI utilization for data analysis in mass spectrometry* $\xrightarrow{\texttt{Equivalent\_To}}$ *Discuss and evaluate the implications of using artificial intelligence for data analysis in mass spectrometry*	0.898

Course	**Relation between Learning Outcomes**	**Sem. sim.**
Digital labour platforms	*Describe and explain the main legal challenges related to the classification of platform workers* $\xrightarrow{\texttt{Possible\_Prerequisite\_Of}}$ *Apply legal knowledge to assess the classification of platform workers in real-world scenarios*	0.862
Item Response Theory	*Describe the purposes and limitations of closed-ended multiple-choice instruments* $\xrightarrow{\texttt{Possible\_Prerequisite\_Of}}$ *Compare multiple-choice instruments with other traditional forms of assessment (open-ended tests, oral tests, practical tests)*	0.852
Item Response Theory II	*Assess the potential extent of the effects of cheating* $\xrightarrow{\texttt{Equivalent\_To}}$ *Evaluate the effectiveness of strategies to combat cheating*	0.853
The use of AI in human resource management	*Construct structured arguments integrating EU, national, and comparative perspectives* $\xrightarrow{\texttt{Equivalent\_To}}$ *Construct structured arguments integrating EU, national, and comparative perspectives*	0.991

Course	Relation between Learning Outcomes	Sem. sim.
What does thinking mean?	*Critically evaluate the role of AI and the web in today's society* $\xrightarrow{\texttt{Possible\_Prerequisite\_Of}}$ *Develop a detailed reflection on the epistemological and social implications of the use of AI and the web*	0.864

Cross-course Degree Distribution Considering exclusively cross-course relations (`intra_course = false`), the analysis of the degree distribution provides insight into the level of integration of individual Learning Outcomes within the UniTo-EDVANCE catalogue as a whole. At catalogue level, the average cross-course degree of Learning Outcomes is equal to 4.08, with a median value of 2, a minimum of 0, and a maximum of 33. This indicates that, on average, each Learning Outcome is connected to approximately four outcomes belonging to other courses, while the majority exhibits a more limited number of cross-course connections. In particular, 119 Learning Outcomes have a cross-course degree equal to zero, meaning that they are connected exclusively within their own course and do not exhibit semantic or cognitive relations with Learning Outcomes from other courses.

The distribution of cross-course degree values is strongly skewed, as shown in Figure 7.8. Most Learning Outcomes are characterised by low to moderate degree values, predominantly between 1 and 6, whereas a small subset concentrates a high number of cross-course connections. The presence of high maximum values, up to 33 connections for a single Learning Outcome, highlights the existence of highly connected nodes that play a central role in the overall structure of the catalogue.

The analysis of Learning Outcomes with the highest cross-course degree confirms the emergence of a semantic backbone. In this context, the term *semantic backbone* refers to the subset of Learning Outcomes that exhibit high cross-course connectivity and act as integrative conceptual elements across different courses, contributing to the global coherence of the catalogue. These Learning Outcomes do not represent formal prerequisites, but rather transversal nodes around which semantic and cognitive relations spanning different disciplinary domains tend to concentrate.

In particular, a Learning Outcome belonging to the course *Digital Pathol-*

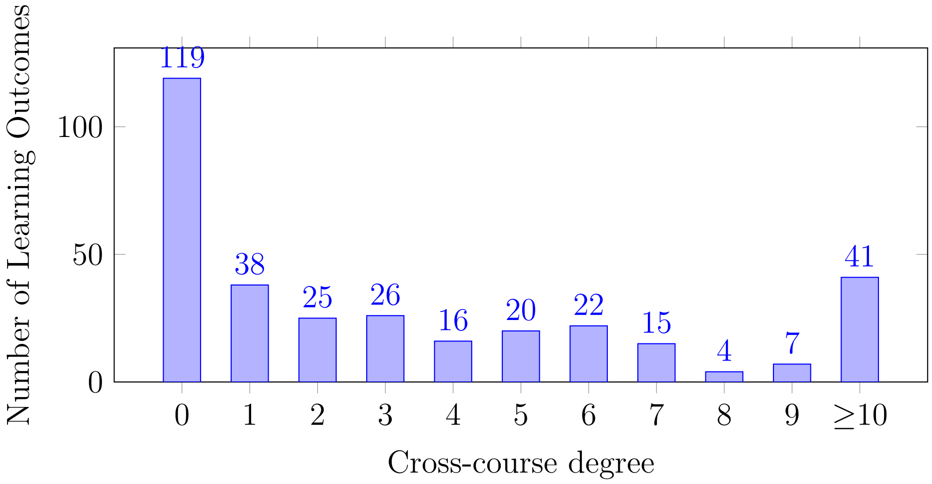

Figure 7.8: Histogram of the cross-course degree distribution of Learning Outcomes in the UniTo-EDVANCE catalogue. High-degree values are aggregated in the ≥10 bin for readability.

ogy and AI for Diagnostic Innovation, focused on the analysis of real clinical case studies and on the evaluation of the integration of artificial intelligence tools in diagnostic support, exhibits the highest cross-course degree value (33), positioning itself as a major connecting node within the catalogue. Similarly, high cross-course degree values, ranging between 24 and 26, are observed for several Learning Outcomes associated with the courses *Precision Oncology: AI-Driven Molecular Diagnostics* and *AI and imaging for cancer*. These outcomes address topics such as the critical evaluation of AI applications in oncology, model validation, the integration of AI-driven solutions into clinical decision support systems, and the ethical, regulatory, and translational implications of their adoption.

Overall, the cross-course degree analysis reveals a catalogue structure characterised by the coexistence of thematically circumscribed Learning Outcomes and a limited number of highly connected objectives that perform an integrative function at catalogue level. This configuration suggests that the UniTo-EDVANCE offer cannot be interpreted as a simple collection of isolated courses, but rather as a learning space in which selected Learning Outcomes contribute substantially to the construction of transversal connections and potentially interconnected learning pathways.

Betweenness Centrality

The analysis of *betweenness centrality* computed on the overall LO–LO graph makes it possible to identify Learning Outcomes that play a role of *structural mediation* in the connectivity of the UniTo-EDVANCE catalogue. Betweenness values exhibit a strongly skewed distribution, with a limited number of Learning Outcomes concentrating a large proportion of shortest paths between pairs of nodes.

Learning Outcomes with the highest betweenness values do not necessarily correspond to those with the highest degree, but rather emerge as nodes capable of connecting otherwise weakly connected regions of the graph. In particular, several highly central Learning Outcomes are formulated in methodological or conceptual terms, such as the description of the principles underlying Artificial Intelligence techniques, the analysis of machine learning model applications, and the application of theoretical models across different analytical contexts. These outcomes often display moderate degree values combined with very high betweenness, indicating that their importance derives from their position as bridges between thematic clusters without relying on dense local connectivity.

Table 7.3 reports the Learning Outcomes with the highest betweenness values in the overall LO–LO graph, together with their degree values. The table highlights how high betweenness can be associated both with moderate-degree nodes, which act as strategic connectors between clusters, and with more densely connected nodes that combine local integration with a global mediating role.

Table 7.3: Top Learning Outcomes by betweenness centrality in the UniTo-EDVANCE catalogue (overall LO–LO graph).

#	**Learning Outcome**	**Degree**	**Betweenness**
1	Describe the concepts underlying the techniques currently used in the field of Artificial Intelligence, and their basic functioning	16	5617.33
2	Analyze an example of a machine learning model application appropriate to the field of analysis	6	5230.04
3	Apply theoretical models according to the type of analysis to be conducted	11	4784.64

#	**Learning Outcome**	**Degree**	**Betweenness**
4	Analyze and interpret the results of statistical tests and the graphical representations of experimental data	13	4066.32
5	Apply machine learning models in the clinical field	18	3759.20
6	Design original training activities related to aspects of Artificial Intelligence	9	3619.16
7	Identify and describe elementary building blocks of machine learning through examples of a simple algorithm	4	3613.29
8	Discuss ethical and regulatory implications of employing intelligent algorithms in human health	21	3550.35
9	Describe and compare different types of short- and long-term risks associated with AI	12	2842.84
10	Independently evaluate the appropriateness of tools with respect to the educational context, linguistic objectives, and student needs	6	2831.90

Restricting the analysis to cross-course relations highlights a more specific form of mediation, directly related to the integration of different courses within the catalogue. Betweenness centrality computed on the cross-course subgraph reveals a small subset of Learning Outcomes that act as transversal connectors across courses. These Learning Outcomes are predominantly associated with themes such as the critical appraisal of AI applications in clinical and oncological settings, the evaluation of risks and limitations of intelligent systems, model validation, and the interpretation of AI-driven decision-support workflows.

Several of these Learning Outcomes exhibit relatively low degree values while maintaining high cross-course betweenness, confirming that their role is not primarily based on the number of direct connections, but on their position along shortest paths linking Learning Outcomes from different courses. As a result, they function as key junctions that enable conceptual continuity across disciplinary boundaries.

Overall, the betweenness analysis confirms that the structure of the UniTo-EDVANCE catalogue is not solely determined by highly connected hubs, but also relies on a limited number of Learning Outcomes that perform a crucial mediating function. These nodes support global cohesion by linking distinct areas of the catalogue and play a central role in sustaining transversal and interdisciplinary learning pathways.

Weighted Shortest Paths

To further investigate the structural organization of the UniTo-EDVANCE catalogue, weighted shortest path analyses were conducted on the Learning Outcome graph, using semantic distance as edge weight, defined as $d = 1 - \text{sem}_{\text{sim}}$. In this context, shortest paths are not interpreted as prescriptive learning sequences, but as indicators of semantic and cognitive proximity within the catalogue.

Shortest Path Distances at Learning Outcome Level. Considering weighted shortest paths computed on a sample of source nodes in the full Learning Outcome graph, the minimum observed distance is equal to 0.0, indicating the presence of pairs of Learning Outcomes connected by near-equivalent semantic relations. The average shortest path distance is 1.98, with a median value of 1.99, while the 90^{th} percentile reaches 3.15. The maximum observed distance is 5.47. These values suggest that, despite the thematic heterogeneity of the catalogue, the overall semantic structure remains relatively compact: most Learning Outcomes can be connected through paths involving a limited number of intermediate concepts and moderate cumulative semantic distance.

Cross-course Semantic Distances. To specifically assess semantic integration across courses, weighted shortest path distances were analysed for pairs of Learning Outcomes belonging to different courses, while allowing paths to traverse the full graph structure. In this case, the minimum observed cross-course distance is 0.12, indicating that some Learning Outcomes from distinct courses are semantically very close. The average cross-course distance is 2.03, with a median value of 2.03, closely aligned with the values observed at the overall Learning Outcome level. The 90^{th} percentile reaches 3.18, while the maximum distance remains 5.47.

The close correspondence between global and cross-course distance statistics indicates that connections between different courses do not introduce substantially larger semantic gaps. Instead, Learning Outcomes from distinct courses remain embedded in a shared semantic space, supporting the interpretation of the UniTo-EDVANCE catalogue as an interconnected design environment and not a collection of isolated instructional units. From a design perspective, this result reinforces the view that cross-course relations contribute meaningfully to the navigability and conceptual coherence of the catalogue without imposing rigid or linear learning trajectories.

7.3 Application on University of Savoie-Mont Blanc BAT-Programme

7.3.1 The BAT Programme

The BAT (Bâtiment Écoconstruction Énergie) Programme is an engineering degree programme offered by Polytech Annecy–Chambéry, focused on sustainable construction, energy systems, and building engineering. The curriculum spans from Semester 5 to Semester 10 and combines foundational scientific training with progressively specialised technical, managerial, and project-based components.

The programme integrates disciplines from civil and structural engineering, building physics, energy systems, materials science, environmental sustainability, and digital construction methods, alongside transversal competences in management, communication, and professional practice. Courses are organised into teaching units that include lectures, practical activities, project-based learning (APP), and mandatory internships, culminating in a final engineering internship.

Within the BAT Programme, each course is associated with multiple explicitly defined Learning Outcomes, articulated at different cognitive levels (Notion, Application, Mastery, and Expertise). This characteristic makes the programme particularly suitable for graph-based analyses at the Learning Outcome level, as it allows the internal semantic organisation of individual courses to be examined in detail. For this reason, the BAT Programme was selected as a case study to investigate intra-course relationships among Learning Outcomes and their structural properties.

It should be noted, however, that the courses in the BAT Programme were not originally designed according to the SPIRAL model. Consequently, the semantic and cognitive relations among Learning Outcomes analysed in this study are not prescribed by the instructional design, but are instead inferred through the proposed representation model and computational analysis framework.

7.3.2 Graph Analysis of the BAT Program

Descriptive Analysis of the BAT Program Graph

The graph constructed from the BAT specialization programme comprises a total of 217 nodes and 421 relationships. As in the EDVANCE case study, the analysis focuses on the subgraph induced by Learning Outcomes (LOs) and the relations among them, in order to investigate the semantic and cognitive structure of the programme independently of its formal didactic organization.

All 157 Learning Outcomes included in the dataset are linked to exactly one course. No LOs are unassociated with a course, nor are LOs shared by more than one course. This one-to-one correspondence reflects a strongly structured curricular design, in which each course is formally responsible for a distinct and non-overlapping set of learning objectives.

Considering only LO–LO relations, the graph contains 264 edges, corresponding to an average of 1.68 connections per Learning Outcome. When restricting the analysis to cross-course relations, 217 edges remain, yielding an average of 1.38 cross-course connections per LO. Overall, these values indicate a moderately connected network in which Learning Outcomes are, on average, linked to more than one other outcome, predominantly across course boundaries.

LO–LO relations are distributed across three relation types: 142 `Connected_To`, 93 `Similar_To`, and 29 `Equivalent_To`. The prevalence of `Connected_To` relations indicates that the network structure is predominantly characterised by relations of progression or dependency, superseding the influence of semantic similarity or equivalence.

A further distinction can be made between intra-course and cross-course relations. Only 47 LO–LO relations are internal to the same course, whereas 217 relations connect Learning Outcomes belonging to different courses. This pattern holds across relation types, with the large majority of `Connected_To`, `Similar_To`, and `Equivalent_To` relations occurring between courses.

The distribution of Learning Outcomes across Bloom's taxonomy levels (coded on a 1–6 scale) is reported in Figure 7.9. Outcomes are strongly concentrated at intermediate cognitive levels, with a clear prevalence of level 3 (*Apply*). Lower and higher levels are less represented, indicating a curriculum primarily oriented toward applied and procedural competences, while still incorporating a non-negligible number of higher-order learning objectives.

A visual overview of the graph structure is provided in Figure 7.10. From a visual perspective, the graph exhibits a highly heterogeneous structure,

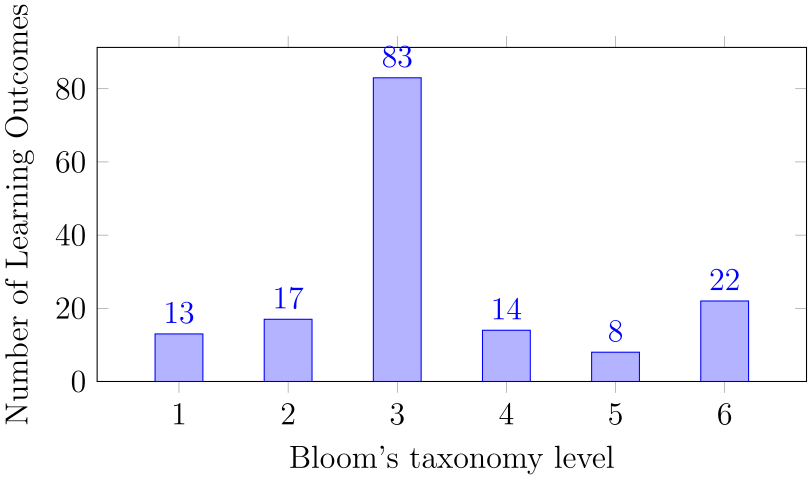

Figure 7.9: Distribution of Learning Outcomes across Bloom's taxonomy levels.

characterised by a densely connected central core surrounded by peripheral branches and isolated components. This configuration suggests a non-uniform distribution of conceptual roles among Learning Outcomes, with a small number of central nodes acting as connective hubs and a majority of peripheral or specialised objectives, in line with the evidence provided by degree, betweenness centrality, and shortest path metrics. The weakly connected components analysis of the BAT catalogue reveals a highly unbalanced structure. Out of all detected components, a single giant component aggregates 163 nodes, encompassing the majority of courses and their associated Learning Outcomes, and forming a cohesive semantic and curricular backbone of the programme. Alongside this dominant structure, several small components are observed, most of them with sizes ranging from 2 to 6 nodes, as well as a limited number of intermediate components (e.g., one component of size 12). These smaller components typically correspond to highly specialised, introductory, or transversal courses whose Learning Outcomes remain semantically self-contained. Overall, this configuration suggests a curriculum structure centred on a strongly integrated core and complemented by peripheral modules with limited conceptual overlap.

Degree Distribution

Intra-course Degree Analysis The intra-course degree analysis focuses on the number of LO–LO relations connecting Learning Outcomes within the same course, providing insight into the internal cohesion of individual

Figure 7.10: Visual representation of the BAT Learning Outcome graph.

teaching units. For each Learning Outcome, the intra-course degree was computed as the number of adjacent LO–LO edges whose endpoints belong to the same course.

Across the entire dataset, the average intra-course degree is 0.60, with a median value of 0, a minimum of 0, and a maximum of 5. Notably, 95 out of 157 Learning Outcomes exhibit an intra-course degree equal to zero, indicating that the majority of outcomes do not maintain explicit semantic or progression-related links with other outcomes within the same course.

This distribution highlights a highly skewed pattern, where intra-course connectivity is concentrated in a limited subset of Learning Outcomes. Only a small number of nodes reach moderate intra-course degree values (between 2 and 5), while most outcomes remain isolated at the course level. This suggests that, in many courses, Learning Outcomes are designed as distinct and non-redundant objectives.

When aggregating intra-course degree values at the course level, substantial heterogeneity emerges. A small group of courses exhibits relatively high internal cohesion, with average intra-course degree values exceeding 2. In particular, courses such as *Créativité et Management de l'innovation* (average intra-degree 3.14, maximum 5), *Matériaux de construction* (2.5), and selected language and construction-related courses show denser internal LO connectivity.

Conversely, a large number of courses display an average intra-course degree equal to zero. These courses include introductory modules, project-based activities, internships, and several technical or transversal units, where Learning Outcomes are either singular or intentionally formulated as independent targets. In such cases, internal cohesion is achieved implicitly through instructional design rather than through explicit LO–LO relations.

Overall, the intra-course degree analysis indicates that internal LO connectivity is not a dominant structural feature of the BAT programme. Cohesion among Learning Outcomes is primarily achieved through cross-course relations and less through connections within individual courses.

Cross-course Degree Analysis and Central Roles The cross-course degree analysis considers the number of relations connecting each Learning Outcome to other Learning Outcomes belonging to different courses, providing a direct measure of curricular integration at the programme scale.

In the BAT programme, the average cross-course degree is 2.76, with a median value of 1, a minimum of 0, and a maximum of 17. Overall, 66 Learning Outcomes exhibit a cross-course degree equal to zero, while the remaining outcomes maintain at least one cross-course connection.

The distribution of cross-course degree values is strongly right-skewed. Alongside many Learning Outcomes with low cross-course connectivity, a long tail of nodes with progressively higher degree values emerges. Several Learning Outcomes reach cross-course degree values between 7 and 14, up to a maximum of 17, identifying a restricted set of highly connected hubs.

These highly connected Learning Outcomes predominantly belong to project-based and technical-construction courses and are associated with activities such as design, technical dimensioning, project evaluation, site management, and regulatory compliance. Their high degree reflects a strong capacity to integrate objectives defined across multiple courses.

While degree centrality highlights hubs, betweenness centrality provides complementary insight into structural mediation. Betweenness values are also concentrated on a limited subset of Learning Outcomes, partially overlapping with hubs but not reducible to them. It is evident that certain learning outcomes demonstrate high betweenness, despite exhibiting a moderate degree. This observation suggests that their significance is attributable to their strategic positioning along shortest paths, as opposed to the number of direct connections they possess.

Taken together, the combined analysis of degree and betweenness reveals that cross-course integration is sustained by a restricted set of Learning Outcomes acting as hubs, bridges, or both. These central outcomes play a key role in ensuring curricular coherence and navigability at the programme level.

Shortest-path Distances

To characterize the navigability and global integration of the Learning Outcomes network, weighted shortest-path distances were computed using Dijkstra's algorithm on the projected graph, where edge weights represent the `distance` associated with each LO–LO relationship.

Across all reachable LO pairs in the global weighted graph (`lo_weighted_global_dist`), shortest-path distances are low and tightly bounded, indicating a compact topology. The average distance is 1.37 and the median is 1.33, while the 90th percentile is 2.32 and the maximum observed distance is 3.76. The minimum value is numerically close to zero and can be interpreted as such.

Focusing on cross-course connectivity, two complementary notions of cross-course distance were considered. When restricting attention to pairs of Learning Outcomes belonging to different courses while computing shortest paths in the full graph, distances remain comparable to the global ones (average 1.47, median 1.37, 90th percentile 2.41), indicating that inter-course traversal requires only a slightly higher cost.

When shortest paths are computed on a graph including only cross-course relations, distances are substantially smaller (average 0.64, median 0.50, 90th percentile 1.33). This result highlights the presence of particularly direct and semantically strong inter-course connections.

Overall, the shortest-path analysis confirms that the BAT Learning Outcomes network is compact and highly navigable, with robust cross-course integration supporting efficient traversal across the programme.

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Chapter 8

Discussion, Conclusions and Future Developments

8.1 Discussion

This discussion focuses on Research Questions RQ1, RQ2, and RQ3, which directly address the pedagogical grounding, structural properties, and evaluative indicators of personalized learning paths. Research Question RQ4, which concerns learner experience and impact, is intentionally left outside the scope of this section and is addressed as a direction for future work.

8.1.1 RQ1 – Limits of Current Personalization Approaches in Digital Learning Environments

Research Question RQ1 aims to investigate which personalization strategies are currently adopted in Digital Learning Environments and to analyse their main strengths and limitations, with particular attention to the elements that are still missing in order to make such strategies pedagogically effective. Recent literature highlights how personalization has become a central objective in digital education, especially in connection with the increasing adoption of adaptive systems, recommender systems, learning analytics, and artificial intelligence techniques. These limitations are consistently reported in the chapter 3 on adaptive learning and recommender systems, where personalization is predominantly driven by behavioural data and optimisation criteria, while pedagogical intent and instructional design transparency remain secondary concerns.

A large portion of existing approaches can be framed within a predominantly *data-centric* paradigm, in which personalization emerges as the outcome of algorithmic processes based on tracking data, learner profiles, behavioural patterns, or similarity measures between users and learning resources. While these strategies have proven effective in terms of scalability, automation, and system-level adaptability, they also present a number of critical issues from a pedagogical perspective.

First, personalization is often *system-driven* instead of intentionally designed. Typically, recommended or adapted learning paths are generated in response to observed data, and not as the result of an explicit instructional design rationale. As a consequence, it may be difficult for instructors and instructional designers to interpret, validate, or justify the decisions taken by the system, reducing the pedagogical transparency of the personalization process.

Second, learning paths are frequently treated as sequences to be optimized, and not as *designed pedagogical objects*. In many adaptive and recommendation-based systems, the structure of learning paths and the relationships between learning outcomes, learning activities, and assessment remain implicit or weakly formalized. Personalization therefore tends to focus on content adaptation or sequencing, while the problem of *pedagogical equivalence* between alternative learning paths is rarely addressed in a systematic way.

A further limitation concerns the role of instructors and course designers. In highly automated personalization models, human intervention is often limited to an initial configuration phase or to a posterior validation of system outputs. Fine-grained pedagogical control over how personalization is implemented is therefore reduced, potentially conflicting with learner-centred and human-in-the-loop paradigms, in which personalization should remain interpretable, negotiable, and context-sensitive.

Overall, the analysis of the literature suggests that, despite their technological sophistication, many current personalization strategies in Digital Learning Environments are only weakly grounded in explicit instructional design models. Personalization thus tends to emerge as a system-level behaviour rather than as an intentional, analyzable, and governable property of course design.

Within this context, there is a clear need for models that integrate data-driven techniques with an explicit pedagogical structuring of learning paths. Such models should enable personalization to be designed, interpreted, and evaluated at the level of instructional design, instead of being delegated entirely to algorithmic decision-making. The SPIRAL model is proposed in response to this need, positioning personalization as a design property of the curriculum and not merely as an emergent effect of data analysis. Within this model, pedagogical effectiveness is interpreted in terms of design transparency, explicit alignment with intended learning outcomes, instructor validation of alternative learning paths, and the possibility of evaluating equivalence and coherence at the structural level.

8.1.2 The role of Course-level Analysis: from the Start@UniTo Case to Ecosystem-oriented Metrics (RQ3)

The Start@UniTo case demonstrates that personalization is not an artificial construct imposed by instructional models, but an intrinsic tendency of learners when interacting with modular digital content. Although the two main case studies discussed in Sections 7.2 and 7.3 explicitly address the analysis of learning paths at catalogue or programme level, Section 7.1 introduces a complementary perspective focused on the level of individual courses situated within a broader digital learning ecosystem. The analysis of the Start@UniTo courses is not intended to study or optimise intra-course personalization. Rather, it provides an empirical context for clarifying which structural conditions must be satisfied for a course to meaningfully contribute to personalized learning paths at ecosystem level.

The Start@UniTo case highlights an environment in which modularity and flexibility emerge spontaneously from learners' interaction patterns. Learning units are accessed in a selective and non-linear manner, showing that even in the absence of an explicit outcome-based instructional design, learners tend to construct individualized trajectories according to their goals and needs. However, this form of personalization remains implicitly tied to usage behaviours and is not supported by a formal pedagogical structure.

From the perspective of RQ3, this aspect is particularly relevant. In the absence of an explicit representation of learning outcomes and of the relationships between them, it is not possible to assess whether different ways of traversing a course correspond to pedagogically equivalent learning experiences. Similarly, it becomes difficult to determine to what extent such trajectories can be meaningfully integrated into broader learning paths that span multiple courses or modules within an ecosystem.

In this sense, the Start@UniTo analysis can be interpreted as a baseline scenario in which personalization exists only as an emergent phenomenon, but is neither intentionally designed nor systematically evaluable. This limitation motivates the introduction of structural indicators capable of analysing courses not as isolated entities, but as interoperable components of an outcome-oriented learning ecosystem.

8.1.3 Designed Personalization and Equivalent Learning Paths in Educational Catalogues (RQ2)

Against this background, the results presented in Section 7.2 show how the SPIRAL model explicitly addresses several of the critical issues emerging from both the literature and the analysis of non-designed contexts. In particular, SPIRAL introduces a notion of personalization that is not based on automatic content adaptation, but on the intentional design of alternative and pedagogically equivalent learning paths with respect to the intended learning outcomes. Equivalence is here understood in an operational and pedagogical sense, referring to alternative learning paths that are aligned with the same intended learning outcomes and validated through instructional design decisions.

In the EDVANCE catalogue, personalization emerges through the identification of multiple valid trajectories leading to the same set of learning outcomes, while differing in terms of the ordering, combination, or granularity of the involved learning units. Equivalence between learning paths is therefore not defined in purely structural terms, but with respect to their capacity to support the achievement of the same educational objectives, consistently with an outcome-oriented design perspective.

This result becomes particularly significant when contrasted with the Start@UniTo case. While flexibility in the latter arises from unconstrained use of learning materials, within the SPIRAL model flexibility is an explicit design property embedded in the macro-design of the catalogue. Personalization does not emerge as a system-level behaviour or as a by-product of learner interaction, but as an intentional characteristic of instructional design.

Within this framework, the learner's role is not to follow an automatically optimised or recommended path, but to choose among pedagogically validated alternatives. Likewise, instructors and instructional designers retain a central role in defining relationships between learning outcomes and in validating equivalence between alternative paths. This positioning is coherent with learner-centred and human-in-the-loop paradigms, in which personalization is supported by data and structural representations, but not delegated entirely to algorithmic decision-making. While computational methods support the identification of candidate relations between learning outcomes, the validation of equivalence and the construction of alternative learning paths remain grounded in pedagogical constraints and instructional design choices.

8.1.4 Structural Indicators for Evaluating Learning Paths at Ecosystem Level (RQ3)

The proposed indicators operate at different but complementary levels: some inform the structural readiness of individual courses to participate in an ecosystem, while others characterise the global properties of the catalogue or programme in which such courses are embedded. Sections 7.3 and 7.2 introduce a set of graph-based metrics that provide a systematic response to RQ3. These metrics are not conceived to drive automatic optimisation or recommendation of learning paths, but to support a design-oriented evaluation of the structures that enable personalization at ecosystem level.

Indicators such as distances between learning outcomes, particularly when computed across courses, provide insights into the connectivity and articulation of educational catalogues. Shorter distances are typically associated with tightly integrated structures, while larger distances suggest a greater diversity of potential trajectories, which may be leveraged to support personalization. The comparison between intra-course and cross-course distances further allows for distinguishing internal course coherence from the openness of the system to transversal learning paths.

Additional insights are provided by analysing the distribution of different relation types between learning outcomes, such as connectivity, similarity, and equivalence relations. The presence of similarity and equivalence relations at cross-course level can be interpreted as an indicator of the catalogue's capacity to offer alternative learning paths that are not only different, but also pedagogically comparable.

Finally, centrality-based indicators allow for identifying learning outcomes that play a structurally significant role within the ecosystem. Such nodes may correspond to foundational concepts, articulation points between different courses, or potential design bottlenecks. In all cases, these indicators support a critical reflection on the structure of the catalogue, enabling designers to assess whether the resulting configuration is coherent with declared personalization objectives.

Taken together, the proposed metrics shift the focus from personalization understood as dynamic adaptation within individual courses to personalization as a designed and structurally controllable property of an outcome-oriented learning ecosystem. Within this perspective, courses are no longer treated as closed instructional units, but as structured components of a broader system, whose readiness to support personalized learning paths can be analysed, compared, and discussed in a systematic manner. From an institutional perspective, these indicators provide actionable support for instructional designers and programme coordinators to assess whether an educational ecosystem is structurally prepared to sustain personalization policies beyond individual course quality. Importantly, the proposed indicators are not intended as performance metrics in a strict evaluative sense, nor as drivers for automatic path optimization. Rather, they function as analytical lenses that support data-informed reflection on learning path design at different levels of abstraction. In this way, the SPIRAL model combines structural rigour with pedagogical flexibility, making personalization an explicit and analysable design property instead of an emergent or opaque system behaviour.

8.2 Conclusions and Future Developments

The work presented in this thesis represents an initial yet structurally grounded step in the development of the SPIRAL model and in the exploration of its potential applications within complex Digital Learning Environments. The results presented show that the SPIRAL model can be effectively employed as a methodological framework for representing, analysing, and designing learning paths within complex learning ecosystems. The integration of inferred relations, graph-based representations, and structural metrics highlights how personalization does not rely on isolated local design choices, but rather emerges from the overall structure of the model and from the relationships among Learning Outcomes.

At the same time, the work carried out in this thesis points to several directions for further development. While the proposed algorithms, representational choices, and analytical metrics proved effective in the analyzed contexts, they can be further extended, refined, and validated at a larger scale. In this perspective, the future works outlined in this section are not intended as marginal extensions of the research, but as natural continuations aimed at consolidating and expanding the contribution of the SPIRAL model at both methodological and applied levels.

A first and central line of future work concerns the *design and implementation of an online editor for course design based on the SPIRAL model.* The main objective of such a tool would be to move beyond the use of the model as an ex-post analytical framework and to support instructors directly during the macro-design phase of course development. The editor would guide teachers in the structured definition of Learning Units, Learning Outcomes, and their relations, enforcing the formal constraints of the SPIRAL model while remaining flexible with respect to pedagogical choices. A key component of this tool would be the integration of an interactive graph-based visualization, allowing designers to observe the emerging structure of the course in real time. Through this visualization, properties such as prerequisite chains, alternative learning paths, and structurally central units would become immediately apparent.

Within this context, the graph metrics investigated in this work would assume a new role. They would function as interpretative indicators available already at design time, supporting instructors in analysing the structural properties of learning paths. By providing feedback on aspects such as connectivity, redundancy, or the concentration of prerequisites, the editor could help identify potential structural weaknesses or missed opportunities for personalization before course deployment. In this perspective, metrics would act as decision-support tools, fostering more informed and reflective instructional design practices.

A second direction for future research involves the continuation and expansion of the experimental work conducted within the EDVANCE project. The analyses presented in this thesis were performed on a limited subset of courses, selected to validate the proposed methodology and indicators. A natural extension consists in applying the same analytical framework to the entire EDVANCE course catalogue. Such a large-scale analysis would make it possible to study the distribution of graph-based metrics across courses of different disciplinary areas and instructional designs, and to identify recurring structural patterns or systematic differences.

Furthermore, extending the analysis to include courses developed by other EDVANCE partners would enable comparative investigations across institutional and cultural contexts. This would open the possibility of studying how different educational traditions and design practices are reflected in the structural properties of learning paths when modeled as graphs. In this perspective, the SPIRAL model could serve not only as a design framework, but also as an analytical lens for comparing and evaluating heterogeneous educational catalogues.

A third line of future work concerns the explicit integration of teachers' expertise in the construction and validation of relationships between Learning Outcomes. In the current work, relationships such as similarity, equivalence, or prerequisite are primarily derived through algorithmic approaches based on semantic similarity and cognitive level. While this enables scalability, it cannot fully replace expert pedagogical judgment. Future developments therefore include the investigation of mechanisms for incorporating a structured form of teacher feedback, for instance through rating, confirmation, or rejection of algorithmically generated relations.

Such an approach would introduce a human-in-the-loop paradigm, in which teachers actively contribute to refining the semantic and pedagogical quality of the graph. Teacher feedback could be used both locally, to improve the coherence of a specific course or catalogue, and globally, to iteratively calibrate the algorithm itself. This would contribute to increased interpretability, trust, and pedagogical validity of the automatically generated structures.

Another promising direction concerns the START platform, which represents a particularly relevant real-world context for applying the SPIRAL model at scale. One possible line of work consists in reorganizing existing content in order to better align it with the SPIRAL framework, for example by redefining Learning Units and making Learning Outcomes more explicit and consistently mapped. Such a reorganization would not only facilitate the application of the model, but also enable systematic empirical analyses of course performance.

In particular, future studies could investigate indicators such as completion rates, average completion time, and dropout distribution, and relate them to the structural properties of the corresponding course graphs. This would make it possible to explore whether specific design features, such as increased modularity or the presence of alternative learning paths, are associated with improved learner engagement and success, thereby strengthening the empirical grounding of the model.

A further line of development involves the integration of the SPIRAL model with educational recommender systems. Once sets of pedagogically equivalent learning paths have been identified through the model, recommendation algorithms could be applied to rank and suggest these alternatives based on user-related information, such as prior performance, learning behavior, or preferences. In this scenario, the role of the SPIRAL model would be to define the space of admissible and pedagogically validated alternatives, while recommender systems would operate within this space to personalize suggestions.

This separation between structural design and adaptive personalization would preserve instructional control while enabling data-driven support for learners. Rather than generating new paths autonomously, recommendation mechanisms would select among existing equivalent options, thus ensuring alignment with the intended learning design.

Finally, an additional application-oriented perspective concerns the use of SPIRAL relations to support learners in situations of difficulty or potential dropout. Relationships such as prerequisite, similarity, and equivalence could be exploited to suggest alternative learning paths or remedial Learning Units when learners encounter obstacles in specific units. In this way, the SPIRAL model could support not only initial personalization, but also dynamic intervention strategies aimed at early detection of difficulties and adaptive learner support throughout the educational process.

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