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Published: 28 June 2024

Citation in BibTeX format

UMAP '24: 32nd ACM Conference on User Modeling, Adaptation and Personalization
July 1 - 4, 2024
Cagliari, Italy

Conference Sponsors:
SIGCHI
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UMAP Adjunct '24: Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization (June 2024)
https://doi.org/10.1145/3631700.3665226
ISBN: 9798400704666

Learner-centered Ontology for Explainable Educational Recommendation

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ABSTRACT

Ontologies form the core of knowledge graphs, which act as faithful, semantic-rich sources for training models in delivering explainable recommendations. These models learn to extract logical paths between learners and resources to be recommended within the knowledge graph, according to behavior- and content-based patterns. Extracted paths are then used not only to provide recommendations, but also to generate accompanying textual explanations. Despite the potential of this approach, current ontologies derived from the traditional learner-resource interaction data fall short in terms of richness from an educational perspective. Conversely, general-purpose ontologies, while comprehensive in educational aspects, are overly complex for recommendation tasks. Unfortunately, a suboptimal ontology might prevent to articulate reasoning paths, and thus explanations, relevant for learners within the knowledge graph. To counter this limitation, in this paper, we propose LOXER, a novel ontology designed to unlock learner-centered logical paths for explainable educational recommendation. Our design integrates insights from diverse sources, including feedback from a local co-design group of learners, observations from specialized traditional large-scale educational recommendation datasets, and connections with well-known vocabularies of other existing ontologies. To validate our ontology, we conducted an evaluation of the explanation types it enables, involving university and lifelong learners and assessing explanation properties like effectiveness, decision-making speed, motivation, satisfaction, and confidence. Results show our ontology's ability to foster diverse considerations during the learners' decision-making process and to establish a semantic structure for knowledge graphs for explainable recommendation.

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UMAP Adjunct '24, July 01–04, 2024, Cagliari, Italy

ACM ISBN 979-8-4007-0466-6/24/07
https://doi.org/10.1145/3631700.3665226

CCS CONCEPTS

• **Information systems → Information systems applications**.

KEYWORDS

Ontology, Recommendation, Explainability.

ACM Reference Format:
Neda Afreen, Giacomo Balloccu, Ludovico Boratto, Gianni Fenu, Francesca Maridina Malloci, Mirko Marras, and Andrea Giovanni Martis. 2024. Learner-centered Ontology for Explainable Educational Recommendation. In *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization (UMAP Adjunct '24), July 01–04, 2024, Cagliari, Italy*. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3631700.3665226

1 INTRODUCTION

Motivation. Educational recommender systems can shape learners' academic and career trajectories by directing them toward pertinent university courses and facilitating lifelong competency development [6]. To offer personalized suggestions, these systems typically utilize learners' historical interactions with educational resources and content-based relationships among the latter. Despite their promising accuracy, the inner workings of existing systems is often opaque to the learner, prompting for more transparent processes [3]. Including explanations in the provided recommendations is essential, not only to promote informed decision-making aligned with individual goals and interests [23] but also to comply with the legal mandate for the right to explanation [11]. Explanations can, in turn, strengthen trust in the system, lead to higher engagement and retention, ignite curiosity, and streamline decision processes [20].

State of the Art. Contemporary recommendation methods strive to enhance transparency by offering textual explanations alongside recommended items [29]. Explanations are created by applying predefined templates or generative methods to reasoning paths within a knowledge graph[1], identified by the recommendation model. To this end, models employ reinforcement learning [2, 18, 26, 27] or language modelling [1, 10], whose effectiveness heavily depends on the semantic structure of the knowledge graph and, hence, the quality (e.g., completeness, expressiveness, and relevance) of the adopted ontology[2] [16]. While tailored ontologies have been defined to build knowledge graphs that enable explainable recommendation in domains like music [2] or cinema [26, 27], the need for ontologies to explain educational recommendations is relatively recent. Initial applications of the above explainable recommendation methods in education have focused on models that merely rely on the implicit ontology inherently embedded into the interaction data used for traditional non-explainable recommendation [9].

Limitations. Ontologies ingrained within the learner-resource interaction data, such as tracking clicks on educational content [9, 25], might lack crucial explanatory aspects like the semantic connections between learning resources and their relevance to subjects, competencies, and occupations. General-purpose ontologies, while covering a broad spectrum of educational details [15, 21], can be excessively fine-grained for explainable recommendation methods, which typically manage paths of limited length. They might also include less relevant details for the recommendation purpose like administrative structures or taxes information. Moreover, existing studies tend not to engage with the end users, i.e., the learners, since the beginning of the design, resulting in ontologies (and so knowledge graphs and explainable recommendations) not aligned with the explanatory aspects that learners find relevant [17, 22]. Hence, there is a need for learner-centered ontologies tailored to explainable recommendation in education.

Our Contributions. In this paper, we propose a Learner-centered Ontology for eXplainable Educational Recommendation (LOXER), to address the limitations of inadequate ontologies in enabling coherent reasoning paths within knowledge graphs for generating relevant explainable recommendations for learners. This ontology is created by standardizing the representation of the educational recommendation domain under a multidisciplinary approach to explainable artificial intelligence in education [5]. In the formulation of our ontology, we integrated insights from various sources, incorporating feedback from a local co-creation group of learners for a preliminary validation. We leveraged observations from existing datasets tailored to traditional educational recommendation [4, 7, 13, 19, 28] to avoid overlooking crucial information for model learning. We also established connections with other (educational) ontologies [14, 15], prioritizing the integration of well-known vocabularies, if feasible, to align with FAIR principles[3].

Subsequently, we conducted a comprehensive evaluation of the explanation types enabled by LOXER under a course recommendation task. Relevant, example meta-paths were defined from our ontology and corresponding explanation templates were created in another stage of local co-design. We then developed a questionnaire encompassing two tasks. Firstly, learners ranked explanations (one for each meta-path) related to a given recommended course, considering their perceived importance in the presented scenario. In the second task, learners individually assessed the same explanations based on seven properties (effectiveness, decision speed, motivation, satisfaction, correction ease, transparency, and confidence boost), coming from prior work on explainable artificial intelligence evaluation [24]. In this stage, we extended the validation to a gender-balanced population of 100 university and lifelong learners from around the world. Our results show LOXER's ability to adhere to learners' decision-making processes and establish a semantic structure for knowledge graphs tailored to explainable recommendations. Our findings also represent a blueprint on the extent to which learners value explanatory factors for different meta-paths, serving as actionable insights for novel, learner-centered recommendation models in this research area.

The subsequent sections of the paper are organized as follows: Section 2 outlines the methodology employed for the development and evaluation of the ontology, with a focus on a learner-centered perspective. Section 3 presents the outcomes of the proposed comprehensive assessment, highlighting various explanation types facilitated by the developed ontology. Lastly, Section 4 offers a synthesis of the findings, acknowledges limitations, and outlines directions for future research.

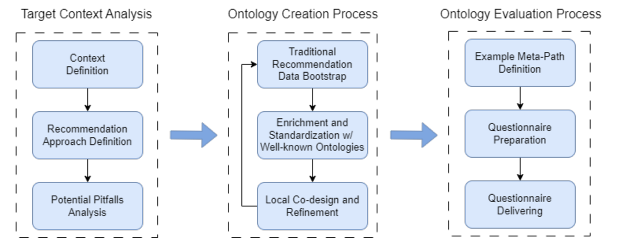

Figure 1: Overview of our methodology. The study begins with an in-depth analysis of the targeted educational context. The ontology creation process involves bootstrapping from traditional recommendation data, enrichment based on existing (educational) ontologies, and local co-design and refinement. The evaluation phase includes defining meta-paths, generating textual explanations through templates, designing questionnaires, and delivering them through Prolific to assess the ontology's effectiveness.

2 METHODOLOGY

In this section, we elaborate on the analysis of the target educational context, the process of creating the ontology, and its evaluation (Figure 1).

2.1 Target Context Analysis

Following the framework for explainable artificial intelligence design in education proposed by [5], our first steps were devoted to depicting the context, the approaches and models, and the potential pitfalls within explainable educational recommendation approaches that leverage knowledge graphs (and so ontologies). Without loss of generalizability, for clarity and conciseness, we consider from now on an educational scenario to address a course recommendation task[4].

[1]A knowledge graph is a structured representation of knowledge that captures entities, their attributes, and relationships in a graph-based format [8].
[2]Ontologies are used to formally model the structure of a system by defining entities, their properties, and relationships; knowledge graphs often incorporate them to establish a standardized framework for organizing and interlinking information [12].
[3]https://joinup.ec.europa.eu/collection/oeg-upm/news/fair-ontologies

[4]Please note that our ontology is general enough to support recommendation tasks for other entities like learning resources and occupations, as well.

Context Definition. Explanations for educational recommendations are integrated into platforms for learners. Therefore, the provided suggestions should primarily resonate with the learners. Without loss of generality, we concentrate on learners within two educational contexts. We consider formal learning scenarios conducted in universities or training organizations, leading to diplomas and certificates. University learners typically fall within the age range of 19 to 27. Adult learners, on the other hand, are generally older and primarily include workers undergoing training as part of their workplace plans. We have also envisioned non-formal learning scenarios for the same learners, outside universities and workplaces, driven more by their intrinsic desire to learn. By encompassing different learning scopes (formal and non-formal) and two types of learners (university and adult), we aim to ensure the generality of our ontology for adoption in various scenarios. Additionally, we plan to analyze how these two factors influence the perception of the explanations facilitated by our ontology.

Recommendation Approach Definition. Path reasoning[5] in explainable recommendation for the target context involves extracting meaningful logical paths between learners and resources within a constructed knowledge graph, following an underlying ontology. Once paths are extracted, they form the foundation for generating textual explanations accompanying recommended resources. For instance, assume to consider an ontology that captures relationships such as course completion and course prerequisites. The recommendation model identifies that the learner completed the course "Introduction to Data Science," which includes the subject "Numpy," that is a prerequisite for the course "Machine Learning for Data Analysis." Based on this path, a corresponding explained recommendation for that learner might be "Consider enrolling in the Machine Learning for Data Analysis course. The Introduction to Data Science course you attended covered the subject of Numpy which serves as a prerequisite for the suggested course." The explanations provide transparent insights into why a particular course is being suggested, offering a clearer rationale grounded in the learner's historical interactions and the ontology's structure.

Potential Pitfalls Analysis. Several potential pitfalls must be considered while developing ontologies for the above explainable recommendation models based on knowledge graphs within the target educational contexts. Overly complex ontologies may hinder interpretability, emphasizing the need for simplicity and clarity in design. Failing to align ontologies with learner expectations can result in misrepresentations, highlighting the importance of learner-centric development. Lack of relevance in recommendation paths may occur if ontologies are not tailored to the educational context, potentially leading to irrelevant explanations. Ontologies must dynamically adapt to evolving learning contexts to avoid becoming outdated, ensuring accuracy and relevance. Additionally, inaccurate or outdated information within the knowledge graph can compromise the integrity of recommendations. Limited coverage of educational aspects may lead to biased suggestions, necessitating a holistic representation of diverse domains. Handling multidisciplinary contexts is crucial, requiring ontologies to integrate seamlessly. Complexity in ontology mapping and ineffective explanations pose challenges that need consideration. Balancing these aspects is vital for the success of ontology-driven, explainable recommendation systems in education.

2.2 Ontology Creation Process

Recognizing potential pitfalls identified in our contextual analysis, we adopted a co-design approach involving collaboration with learners and instructors throughout the conceptualization, development, and validation phases. Our local group, consisting of two university students, two doctoral students, and three experienced researchers in teaching, played a crucial role in this process. To bootstrap the initial version of the ontology, we leveraged information from state-of-the-art, public, large-scale datasets specifically designed for recommendation tasks, including `COCO` [7], `MOOCube` [28], `MOOPer` [19], `EduKG` [13], and `PEEK` [4]. Our goal was to identify relevant yet common entities, relationships, and properties, resolving vocabulary conflicts, and ensuring that less frequent but significant elements of the educational domain were duly incorporated.

With this ontology version, we progressed to the integration phase by establishing connections with other educational ontologies. We prioritized the inclusion of well-known vocabularies, with a specific focus on concepts from ontologies such as [14, 15], ensuring alignment with FAIR principles. This strategic integration resulted in a robust and interconnected ontology, significantly enhancing its potential for widespread use and alignment with established standards in the educational domain. Throughout the integration phase with other educational ontologies, we maintained active involvement with our local co-design group. This iterative, participatory approach contributed to the ontology's refinement and adaptation, making it an effective tool for explainable recommendation.

In our resulting educational ontology[6], the `Learner` takes center stage, embodying the protagonist on a quest for specialized knowledge or skills. This personalized approach caters to the unique needs of each individual learner. Academic or training paths are represented by `Course`, emphasizing recommendations tailored to individual learners. Diverse educational content, labeled as `Learning Resource`, encompasses videos, fragments, chapters, and exercises. Interactions between learners and these resources provide valuable insights into preferences and engagement patterns. Another building block of our educational ontology are `Subject`, spanning topics. Beyond individual learning, our ontology considers the broader context, acknowledging `Institution` as educational organizations, `Instructor` as guiding figures, and `Occupations` as real-world applications of acquired knowledge. The connections within the ontology breathe life into entities. The `interacted` relation captures dynamic engagement, shaping a personalized learning profile. The `is_parent_of` relation introduces hierarchy, aiding in navigating knowledge levels. Prerequisites, highlighted by the `pre_requisite` relation, form a structured learning path. Our ontology also included the `covers` relation, offering a nuanced understanding of cognitive levels. Figure 2 provides a schematic overview of the ontology.

[5] Our choice was motivated by the fact that path-reasoning methods have been proven to achieve the best trade-off between utility and explainability [2].

[6] https://u.garr.it/sWjhQ

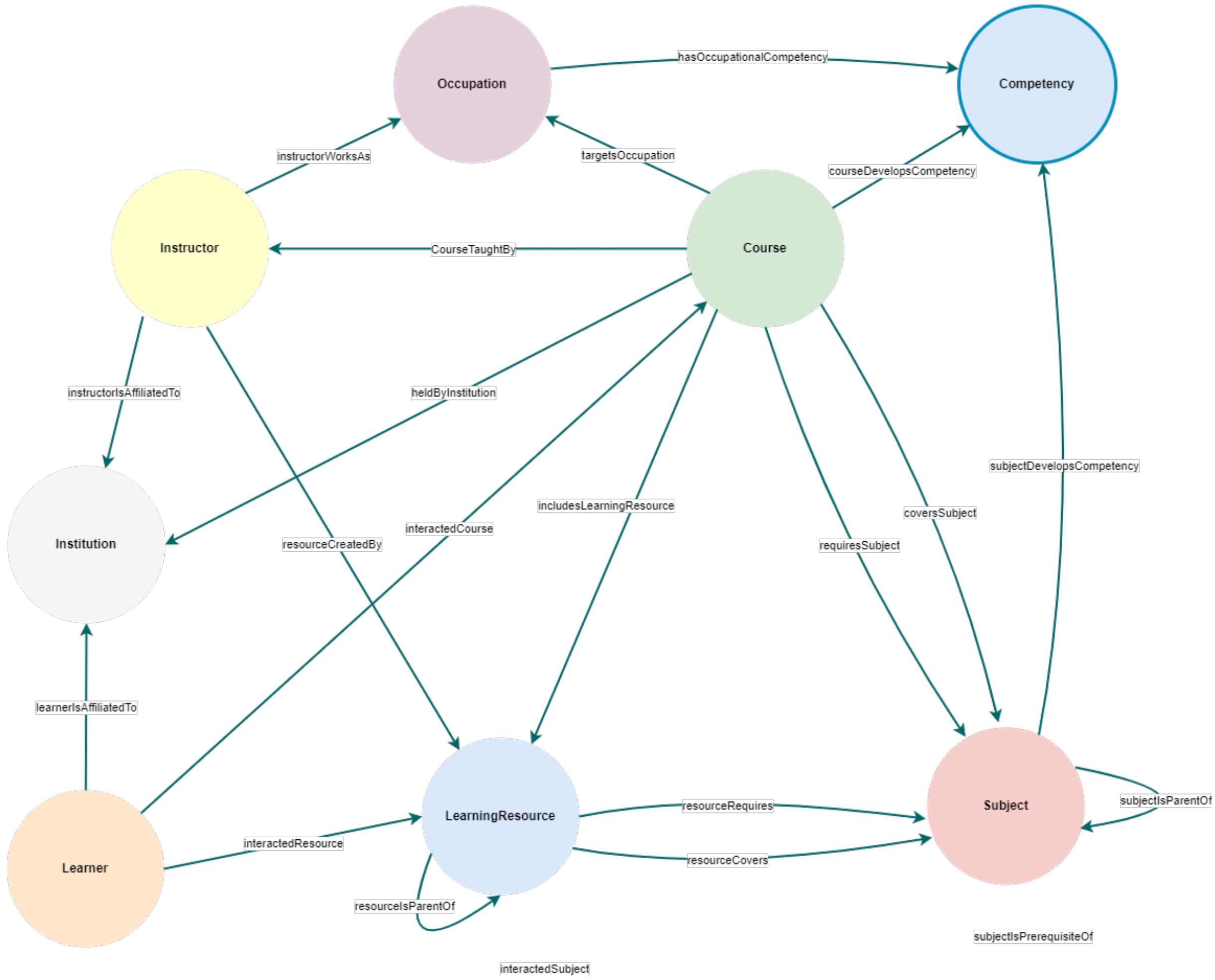

Figure 2: Schematic ontology representation. We summarize the ontology proposed in this study, obtained by formally defining entities, their properties, and relationships. For conciseness, we removed the list of entity properties from this schematic view.

In essence, our ontology is a dynamic framework designed to understand the educational journey, recommend personalized specializations, and provide transparent explanations rooted in learner interactions, preferences, and the semantics of educational content. By embracing the learner as the central character, it aims to foster a tailored learning path that aligns with individual needs.

2.3 Ontology Evaluation Process

Example Meta-Path Definition. In our investigation, we delved into meta-paths in our ontology, which represent specific patterns of relationships between entities. Specifically, we explored the meta-path "learner - enrolled in - course - held by - institution," signifying the connection between a learner and an institution through their course enrollments. Focusing on meta-paths with a learner as the head and a specialization as the tail, we selected 12 significant paths based on their relevance and number of hops involved. This meta-path extraction was conducted with the same local group of learners who actively participated in the co-design phases, ensuring a consistent and contextually relevant representation. These paths were categorized into *extrinsic* and *intrinsic* motivational factors, where *extrinsic* factors involve community influence, and *intrinsic* factors encompass personal interest, historical knowledge, learning outcomes, and learning goals. We associated each meta-path with an explanation motivating why a course was recommended. These explanations, designed for both *extrinsic* and *intrinsic* motivations, aim to provide transparent insights into the rationale behind each recommendation. Figure 3 describes the example meta-paths.

Questionnaire Preparation. We created a fifteen-minute questionnaire[7] with an introductory section explaining its purpose and motivation. Participants provided anonymous responses, and data confidentiality was maintained through coded identification. The study primarily explored learner preferences for receiving course explanations based on either extrinsic factors, influenced by the community, or intrinsic factors, such as interest, historical knowledge, learning outcomes, and learning objectives. In a first part, participants ranked these explanations in order of effectiveness, depending on their motivation, whether studying for pleasure or

[7]https://u.garr.it/ZJHfM

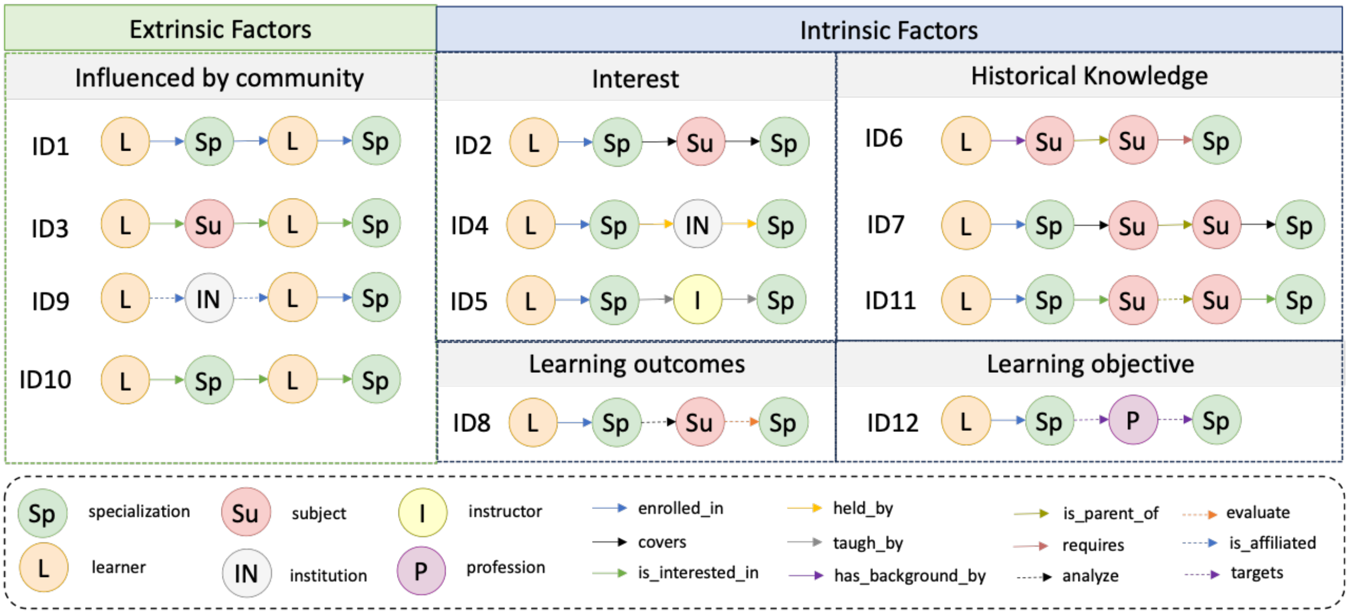

Figure 3: Illustration of example meta-paths in our ontology. Relevant meta-paths, with learners as heads and courses as tails, extracted by involving the same local co-design participants. Categorization into *extrinsic* (e.g., community influence) and *intrinsic* factors (e.g., personal interests) was done.

Table 1: Example explanation from meta-paths in our ontology. For each meta-path described in Figure 3, we provide an example explanation that can be derived. These textual explanations are adopted during the ontology evaluation process.

Meta-Path ID	Derived Example Textual Explanation
ID1	Learners similar to you, who attended the Programming course, have found it to be a valuable complement.
ID2	It covers the topic of object-oriented programming, aligning with content from the Programming course you attended.
ID3	It has been successfully completed by another learner who shares your interest in object-oriented programming.
ID4	It is offered by the same institution, the University of London, from which you previously attended the Programming course.
ID5	It is taught by the same instructor, Mark Bowle, with whom you previously attended the Programming course.
ID6	Your background in object-oriented programming, relevant to Java language, serves as a suitable prerequisite for this course.
ID7	It can amplify your understanding about computational complexity, going beyond its subtopic of program organization and design covered in the Programming course you attended.
ID8	It can advance your skills in basic notions of computational complexity from the analytical level (e.g., identifying algorithmic time complexity) gained in the Programming course to the evaluation level (e.g., comparing and selecting optimal algorithms).
ID9	Another learner from your institution, the University of London, has successfully completed the course.
ID10	Learners who share your interest in the Programming course have also expressed interest in this course.
ID11	Learners who share your interest in the Programming course have also expressed interest in this course.
ID12	To enhance expertise for the software engineer role. This complements the content of the Programming course on the same role.

earning credits. The second part of the questionnaire focused on evaluating explanations derived from each meta-path individually, considering seven criteria proposed by [24]: decision speed, motivation, satisfaction, correction ease, transparency, and confidence boost. Specifically, to facilitate this process, six scenarios were presented, each involving a pairwise comparison of two explanations. Participants used a 5-point Likert scale to express their agreement with each explanation. The scenarios covered various factors like community influence, interest, historical knowledge, instructor influence, institution influence, learning outcomes, learning objectives, and prerequisite knowledge.

Questionnaire Delivering. We recruited 100 participants through Prolific [8], ensuring a balanced gender distribution. Participants were diverse, representing various countries. The cohort was devised to include an equal number of university learners (50) and lifelong learners (50). Further segmentation was carried out within each group, resulting in two subgroups of 25 participants each. This division was instilled into the questionnaire by randomly assigned learners into two different scenarios: learning-for-pleasure and learning-for-credits. In the learning-for-pleasure scenario, participants were motivated by the joy of learning a new topic of interest. In the learning-for-credits scenario, participants aimed to earn

[8]www.prolific.com

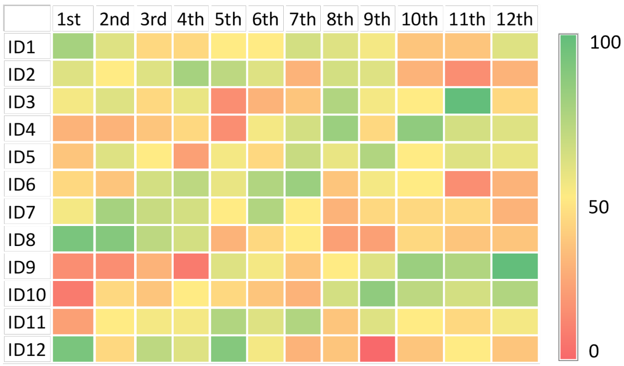

Figure 4: Heatmap illustrating ranked explanations. The y-axis displays unique explanations identified by their respective IDs, while the x-axis indicates ranking positions from first to twelfth. Each cell's color corresponds to the main variable's value within its range, from red (0%) to green (100%).

credits by enrolling in a course. Except for this, the questionnaire content was the same across all participants.

3 EXPERIMENTAL RESULTS

For a learner-centered ontology assessment, we target two research questions:

- **RQ1**: To what extent are meta-paths from our ontology and their corresponding textual explanations effective in aiding course selection?
- **RQ2**: How do learners perceive different types of meta-paths and the explanations derived from our ontology across explanation criteria?

3.1 Perceived Meta-Paths Importance (RQ1)

In our initial analysis, we explored the effectiveness of the example meta-paths and their associated textual explanations in assisting learners with course selection. To this end, we considered the answers given by learners to the ranking task included in the questionnaire, considering their perceived importance of the explanations in the presented scenario. The heatmap presented in Figure 4 illustrates the outcomes of this analysis across the entire study population. The y-axis represents different explanations, each assigned a unique ID (Table 1). On the x-axis, positions from first to twelfth are marked, indicating the ranking of these explanations. Each column in the heatmap is color-coded to represent the percentage of learners who ranked the explanations in that particular position. The color spectrum ranges from red (indicating 0%) to green (indicating 100%).

In the first position, the explanation *"to enhance your expertise for the . . . role. This complements the content . . . the course related to the same role"* with 19% highlights the importance learners attribute to clear and defined objectives. This may indicate a desire for clarity and direction in the learning path, suggesting learners appreciate explanations aligned with potential occupations.

The second position, occupied by the explanation *"It can advance . . . notions of computational complexity from the analytical level (e.g., . . .) gained in the Programming course to the evaluation level (e.g., . . .)"* with 18%, underscores learners' notable interest in attaining tangible educational outcomes. This inclination may be interpreted as a quest for explicit feedback and assessments of their progress, signifying an emphasis on measurable aspects of learning.

The third position, claimed by the explanation *"It can amplify your understanding about. . . , going beyond . . . covered in the Programming course you attended;"* with 15%, suggests that learners prioritize expanding their knowledge into new areas while building upon a strong foundation. From a technical standpoint, this preference shows the significance of incorporating relationships such as *(subject, is_parent_of, subject)* and *(subject, requires, subject)* into the ontology, along with relationships related to the Bloom's Taxonomy. This favors *content-based* over *community-based* explanations.

The analysis of answers for formal and informal learning reveals distinct priorities among university learners in different contexts. In formal settings, where learning for pleasure is emphasized, preferences lean towards learning objectives. Conversely, when the aim is to attain educational credits, interests take precedence (16%). This adaptability implies that learners shift their focus based on the learning scenario. However, the importance of tailoring explanations to learners' professional profiles, particularly in early university experiences, highlights the potential role of an explainable recommendation as a guidance throughout various stages of their academic journey. In a professional context, when focused on formal learning, the second position is claimed by an extrinsic factor, with 20% favoring the explanation *"It has been successfully completed by another learner..."*. This suggests that, driven by external motivation, workers prioritize swift certification to meet professional requirements, making *community-based* explanations more effective for course selection in this scenario.

Findings from RQ1. *The ontology facilitates effective course selection for learners by offering impactful meta-paths and textual explanations, driven by preferences for clear objectives, measurable outcomes, and a focus on expanding knowledge. This adaptability extends to various learning contexts, while a notable inclination towards community-based explanations emerges, especially in professional formal learning scenarios.*

3.2 Multi-Criteria Meta-Path Assessment (RQ2)

We conducted an investigation to identify the preferred explanations and their perceived benefits through a pair-wise comparison focused on effectiveness, decision speed, motivation, satisfaction, correction ease, transparency, and confidence boost. In our statistical analysis of Likert scale responses, we computed weighted mean scores ($\bar{X}$), standard deviations (σ), and frequencies (f). The Likert scales were weighted with averages calculated from *strongly disagree* (1) to *strongly agree* (5), using a length of 0.80 (4/5) to represent the four distances between numbers on the five-point Likert scale. Table 2 summarizes the results.

UC1 Learner connection (`ID01`) - Content connection (`ID02`). In this scenario, the first recommendation (`ID01`) suggests a course based on the enrollment of a user similar to the learner, while the second advises the course because it delves into a topic of object-oriented programming previously encountered in another course (`ID02`). The $\bar{X}$ and σ highlight that, for each criterion, the predominant response is *agree*, except for transparency, where the

Table 2: Pair-wise comparison of explanations and their perceived benefits. We conducted a statistical analysis of Likert scale responses, presenting results with weighted mean scores ($\bar{X}$), standard deviations (σ), and frequencies (f).

	UC1						**UC2**					
	$\bar{X}$		σ		Attitude		$\bar{X}$		σ		Attitude	
	ID01	ID02	ID01	ID02	ID01	ID02	ID03	ID06	ID03	ID06	ID03	ID06
Effectiveness	3,16	3,20	0,94	0,88	A	A	3,02	3,23	0,97	0,92	A	A
Decision Speed	2,93	3,23	0,97	0,85	A	A	2,89	3,27	1,02	0,85	A	A
Motivation	3,06	3,25	0,97	0,98	A	A	2,87	3,36	0,97	0,84	A	A
Satisfaction	3,09	3,21	1,00	1,03	A	A	2,88	3,24	1,00	0,78	A	A
Correction Ease	3,00	3,05	1,04	0,96	A	A	2,88	3,22	1,09	1,00	A	A
Transparency	3,21	3,45	1,00	0,98	A	**SA**	3,13	3,51	0,97	0,81	A	**SA**
Confidence Boost	3,14	3,24	1,00	1,00	A	A	3,01	3,36	0,95	0,84	A	A
	UC3						**UC4**					
	$\bar{X}$		σ		Attitude		$\bar{X}$		σ		Attitude	
	ID04	ID05	ID04	ID05	ID04	ID05	ID07	ID08	ID07	ID08	ID07	ID08
Effectiveness	3,19	2,91	0,95	1,02	A	A	3,11	3,45	0,91	0,81	A	**SA**
Decision Speed	3,22	2,84	0,91	1,01	A	A	3,14	3,33	0,91	0,90	A	A
Motivation	3,11	2,90	0,94	1,07	A	A	3,05	3,40	0,87	0,84	A	A
Satisfaction	3,14	2,89	1,02	1,06	A	A	3,20	3,42	0,92	0,88	A	**SA**
Correction Ease	3,17	2,87	1,11	1,08	A	A	3,21	3,45	0,88	0,91	A	**SA**
Transparency	3,17	3,16	1,03	1,07	A	A	3,32	3,51	0,87	0,88	A	**SA**
Confidence Boost	3,27	2,96	0,96	0,98	A	A	3,24	3,39	0,87	0,89	A	A
	UC5						**UC6**					
	$\bar{X}$		σ		Attitude		$\bar{X}$		σ		Attitude	
	ID12	ID11	ID12	ID11	ID12	ID11	ID09	ID10	ID09	ID10	ID09	ID10
Effectiveness	3,36	3,02	0,85	0,94	A	A	2,69	2,84	1,14	0,97	A	A
Decision Speed	3,35	3,11	0,82	0,96	A	A	2,61	2,86	1,18	1,03	A	A
Motivation	3,40	3,11	0,85	0,86	**SA**	A	2,74	2,91	1,18	1,06	A	A
Satisfaction	3,24	3,12	0,75	0,92	A	A	2,72	2,79	1,15	1,00	A	A
Correction Ease	3,27	3,12	0,85	0,94	A	A	2,70	2,87	1,16	1,05	A	A
Transparency	3,47	3,30	0,73	0,77	**SA**	A	2,91	3,02	1,12	1,08	A	A
Confidence Boost	3,35	3,07	0,77	0,81	A	A	2,77	2,87	1,18	1,05	A	A

$\bar{X}$ (3.45) for the second recommendation categorizes it as *strongly agree*. Additionally, the latter obtained a higher score in terms of motivation (45 occurrences). From the results, the intrinsic factor motivates more strongly compared to the extrinsic factor. The learners' preference for recommendations centered around intrinsic aspects emphasizes the importance of personalization and individual relevance.

UC2 Common interest (`ID03`) - Knowledge prerequisite (`ID06`). In this scenario, the *subject* entity, represented by *object-oriented programming*, is compared in two distinct scenarios: one based on shared interest (`ID03`) and the other on historical knowledge (`ID06`). The second explanation is perceived as more beneficial across all evaluated criteria, especially in terms of transparency ($\bar{X} = 3.51$) and motivation (47 occurrences). These findings highlight the significance for learners to follow a learning path aimed at reinforcing previously acquired knowledge rather than enrolling in a course merely because someone with similar interests has done so. This emphasizes that the decision-making process for choosing a learning path should be motivated by the desire to enhance existing expertise, rather than influenced by behaviors/choices of others.

UC3 Common instructor (`ID04`) - Common Institution (`ID05`). In this scenario, we are assessing two distinct types of explanations, one based on the similarity of the instructor (`ID04`) and the other on the institution (`ID05`). The first explanation is favored, surpassing the second in terms of effectiveness (46 occurrences) and correction ease (45 occurrences). However, it is perceived moderately in relation to motivation. In contrast, the second explanation stands out for confidence boost, with *strongly agree* occurring 39 times. While both instructor and institution are deemed important, the former was more impactful in understanding their appreciation for the decision-making process.

UC4 Subject knowledge (`ID07`) - Cognitive knowledge (`ID08`). In this comparison, we assess the impact of consolidating prior knowledge (`ID07`) against the anticipated outcomes of the learning process expressed through Bloom's Taxonomy (ID08). The first explanation is perceived as moderately useful across all evaluated criteria. In contrast, the second explanation receives a rating of *strongly agree* in terms of effectiveness ($\sigma = 3.45$), satisfaction ($\sigma = 3.42$), correction ease ($\sigma = 3.45$), and transparency ($\sigma = 3.51$). These findings suggest that learners may particularly value explanations that offer a tangible understanding of learning outcomes compared to more general objectives.

UC5 Occupation objective (ID12) - Knowledge prerequisite (ID11). In this context, we compare the overall instructional intent, which focuses on specific topics for the preparation of a software engineer (ID12), with the depth of prior knowledge regarded as prerequisites for the recommended course (ID11). The first explanation receives, on average, a rating of *strongly agree* in terms of motivation ($\bar{X} = 3.4$) and transparency ($\sigma = 3.47$), while in other instances, it is perceived as *agree*, particularly for satisfaction, with 47 occurrences. In the second explanation, it is classified as *agree*, and noteworthy scores are observed for satisfaction (42 occurrences) and confidence boost (47 occurrences). Both explanations are deemed significant based on the considered criteria.

UC6 Common institution (ID09) - Common learner (ID10). In this context, we are evaluating two different types of explanations based on either the similarity of the institution (ID09) or the learner (ID10). Both explanations received an overall rating of *agree*, implying a general consensus among respondents. However, despite this agreement, the evaluations show a balanced distribution between negative and positive responses for both explanations. This suggests that neither type of explanation has a pronounced impact on the explanation properties we assessed. Moreover, results indicate that these explanations have limited effectiveness in motivating users to enroll in recommended courses.

Findings from RQ2. *Learners perceive different meta-paths and explanations from the ontology in a positive manner for all the explanation criteria. While certain types, such as those based on instructors and tangible learning outcomes, show higher impact, others, like institution and common learner interest, exhibit more balanced effectiveness with limited impact on motivation.*

4 CONCLUSION AND FUTURE WORK

In conclusion, our study addressed the growing importance of ontologies for explainable educational recommendation. Despite their growing importance, existing ontologies for this purpose face challenges related to sufficiency and coherence, which hinder their effective use in explaining recommendations. To overcome these limitations, we proposed LOXER, a learner-centered ontology designed for both formal and non-formal education. Our approach saw the construction of a comprehensive, interdisciplinary, and flexible pipeline to transform and expand traditional educational recommendation datasets. Through a qualitative evaluation, we showed the practicality of LOXER in enabling meaningful explanations for recommendations across educational scopes and learner populations.

In our future works, we envision transforming traditional educational datasets into comprehensive knowledge graphs using the proposed ontology, enriching them with external resources for a more holistic representation. Additionally, a reproducibility study is planned to assess existing explainable recommendation models across different domains when applied within the LOXER-based knowledge graph. We aim to conduct an extensive online evaluation to gauge the practical utility of the resulting recommendations and explanations, providing insights into how learners benefit from the explanations. Furthermore, we intend to explore the integration of large language models to generate textual explanations optimized to meet the seven explanation properties we covered, starting from the extracted paths. Lastly, we plan to extend our models to situations where learners lack prior interactions, requiring the development of elicitation processes for connecting their preferences within knowledge graphs enabled by LOXER.

ACKNOWLEDGMENTS

We acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.5 - Call for tender No.3277 published on December 30, 2021 by the Italian Ministry of University and Research (MUR) funded by the European Union – Next Generation EU. Project Code ECS0000038 – Project Title eINS Ecosystem of Innovation for Next Generation Sardinia – CUP F53C22000430001- Grant Assignment Decree No. 1056 adopted on June 23, 2022 by the MUR.

REFERENCES

[1] Giacomo Balloccu, Ludovico Boratto, Christian Cancedda, Gianni Fenu, and Mirko Marras. 2023. Faithful Path Language Modelling for Explainable Recommendation over Knowledge Graph. *CoRR* abs/2310.16452 (2023). arXiv:2310.16452
[2] Giacomo Balloccu, Ludovico Boratto, Gianni Fenu, and Mirko Marras. 2023. Reinforcement recommendation reasoning through knowledge graphs for explanation path quality. *Knowl. Based Syst.* 260 (2023), 110098.
[3] Jordan Barria-Pineda. 2020. Exploring the Need for Transparency in Educational Recommender Systems. In *Proc. of ACM UMAP 2020*. ACM, 376–379.
[4] Sahan Bulathwela, Maria Perez-Ortiz, Erik Novak, Emine Yilmaz, and John Shawe-Taylor. 2021. Peek: A large dataset of learner engagement with educational videos. *arXiv preprint arXiv:2109.03154* (2021).
[5] Blerta Abazi Chaushi, Besnik Selimi, Agron Chaushi, and Marika Apostolova. 2023. Explainable Artificial Intelligence in Education: A Comprehensive Review. In *Proc. of xAI 2023*, Vol. 1902. Springer, 48–71.
[6] Felipe Leite da Silva, Bruna Kin Slodkowski, Ketia Kellen Araújo da Silva, and Sílvio César Cazella. 2023. A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities. *Educ. Inf. Technol.* 28, 3 (2023), 3289–3328.
[7] Danilo Dessì, Gianni Fenu, Mirko Marras, and Diego Reforgiato Recupero. 2018. Coco: Semantic-enriched collection of online courses at scale with experimental use cases. In *Proc. of WorldCIST 2018*. Springer, 1386–1396.
[8] Lisa Ehrlinger and Wolfram Wöß. 2016. Towards a Definition of Knowledge Graphs. In *Proc. of SEMANTiCS 2016 (CEUR Workshop Proceedings, Vol. 1695)*. CEUR-WS.org.
[9] Jibril Frej, Neel Shah, Marta Knezevic, Tanya Nazaretsky, and Tanja Käser. 2023. Finding Paths for Explainable MOOC Recommendation: A Learner Perspective. *CoRR* abs/2312.10082 (2023). arXiv:2312.10082
[10] Shijie Geng, Zuohui Fu, Juntao Tan, Yingqiang Ge, Gerard de Melo, and Yongfeng Zhang. 2022. Path Language Modeling over Knowledge Graphsfor Explainable Recommendation. In *Proc. of WWW 2022*. ACM, 946–955.
[11] Bryce Goodman and Seth R. Flaxman. 2017. European Union Regulations on Algorithmic Decision-Making and a "Right to Explanation". *AI Mag.* 38, 3 (2017), 50–57.
[12] Nicola Guarino, Daniel Oberle, and Steffen Staab. 2009. What Is an Ontology? In *Handbook on Ontologies*. Springer, 1–17.
[13] Nicolas Hubert, Armelle Brun, and Davy Monticolo. 2022. New Ontology and Knowledge Graph for University Curriculum Recommendation. In *Proc. of ISWC 2022*.
[14] Andrew Iliadis, Amelia Acker, Wesley Stevens, and Sezgi Başak Kavakli. 2022. One schema to rule them all: How Schema. org models the world of search. *Journal of the Association for Information Science and Technology* (2022).

[15] Eleni Ilkou, Hasan Abu-Rasheed, MohammadReza Tavakoli, Sherzod Hakimov, Gábor Kismihók, Sören Auer, and Wolfgang Nejdl. 2021. EduCOR: An Educational and Career-Oriented Recommendation Ontology. In *Proc. of ISWC 2021*, Vol. 12922. Springer, 546–562.

[16] Shaoxiong Ji, Shirui Pan, Erik Cambria, Pekka Marttinen, and Philip S. Yu. 2022. A Survey on Knowledge Graphs: Representation, Acquisition, and Applications. *IEEE Trans. Neural Networks Learn. Syst.* 33, 2 (2022), 494–514.

[17] Harry X. Li, Gabriel Appleby, Camelia Daniela Brumar, Remco Chang, and Ashley Suh. 2024. Knowledge Graphs in Practice: Characterizing their Users, Challenges, and Visualization Opportunities. *IEEE Trans. Vis. Comput. Graph.* 30, 1 (2024), 584–594.

[18] Danyang Liu, Jianxun Lian, Zheng Liu, Xiting Wang, Guangzhong Sun, and Xing Xie. 2021. Reinforced Anchor Knowledge Graph Generation for News Recommendation Reasoning. In *Proc. of KDD 2021*. ACM, 1055–1065.

[19] Kunjia Liu, Xiang Zhao, Jiuyang Tang, Weixin Zeng, Jinzhi Liao, Feng Tian, Qinghua Zheng, Jingquan Huang, and Ao Dai. 2021. MOOPer: A Large-Scale Dataset of Practice-Oriented Online Learning. In *Proc. of CCKS 2021*. Springer, 281–287.

[20] Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artif. Intell.* 267 (2019), 1–38.

[21] Nur W. Rahayu, Ridi Ferdiana, and Sri Suning Kusumawardani. 2022. A systematic review of ontology use in E-Learning recommender system. *Com. Ed. Art. Int.* 3 (2022), 100047.

[22] Kristian Stancin, Patrizia Poscic, and Danijela Jaksic. 2020. Ontologies in education - state of the art. *Educ. Inf. Technol.* 25, 6 (2020), 5301–5320.

[23] Nava Tintarev and Judith Masthoff. 2007. A Survey of Explanations in Recommender Systems. In *Proc. of ICDE 2007*. IEEE Computer Society, 801–810.

[24] Nava Tintarev and Judith Masthoff. 2007. A survey of explanations in recommender systems. In *Proc. of ICDEW 2007*. IEEE, 801–810.

[25] Linjing Wu, Qingtang Liu, Wanlei Zhou, Gang Mao, Jingxiu Huang, and Huan Huang. 2020. A Semantic Web-Based Recommendation Framework of Educational Resources in E-Learning. *Technol. Knowl. Learn.* 25, 4 (2020), 811–833.

[26] Yikun Xian, Zuohui Fu, S. Muthukrishnan, Gerard de Melo, and Yongfeng Zhang. 2019. Reinforcement Knowledge Graph Reasoning for Explainable Recommendation. In *Proc. of SIGIR 2019*. ACM, 285–294.

[27] Yikun Xian, Zuohui Fu, Handong Zhao, Yingqiang Ge, Xu Chen, Qiaoying Huang, Shijie Geng, Zhou Qin, Gerard de Melo, S. Muthukrishnan, and Yongfeng Zhang. 2020. CAFE: Coarse-to-Fine Neural Symbolic Reasoning for Explainable Recommendation. In *Proc. of CIKM 2020*. ACM, 1645–1654.

[28] Jifan Yu, Gan Luo, Tong Xiao, Qingyang Zhong, Yuquan Wang, Wenzheng Feng, Junyi Luo, Chenyu Wang, Lei Hou, Juanzi Li, et al. 2020. MOOCCube: a large-scale data repository for NLP applications in MOOCs. In *Proc. of ACL 2020*. 3135–3142.

[29] Yongfeng Zhang and Xu Chen. 2020. Explainable Recommendation: A Survey and New Perspectives. *Found. Trends Inf. Retr.* 14, 1 (2020), 1–101.