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# Digital Brick: Enhancing the Student Experience Using Blockchain, Open Badges and Recommendations

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**Abstract:** The main purpose of this work is to describe the process of design and implementation of a novel e-Learning platform, named Digital Brick, intended to enhance the students' experience in obtaining formal certifications of their competencies. The research method we followed starts form a deep study of the state of the art that showed us the need to invest more research effort on delivering open and flexible online environments to enable students in finding and passing courses with final formal certifications of learning. To reach this goal, we (i) designed a complete system architecture around a standard (SCORM compliant) learning management system in order the approach should be reusable as much as possible. We (ii) introduced specific modules to separate responsibilities on the definition and issuing of formal certifications using digital badges according to the IMS Open Badges standard. We (iii) exploited blockchain technology to make the sharing of badges among actors more secure, transparent and open. Finally, we (iv) introduced a new recommendation algorithm based on machine learning techniques to give advice to students about study materials and learning paths. We spent a significant part of our effort carrying out both a functional and quantitative validation of our proposal. The obtained results are presented through a laboratory case study that involves all the components of the architecture, and the outcomes are discussed providing numerical performance indicators. In conclusion, the resulting platform introduces digital badges and blockchain as tools to share recognized achievements among earners and issuers, and machine learning algorithms to provide students with recommendations on the learning material, learning objects, courses and learning paths more suitable for their learning styles.

**Keywords:** open badges; blockchain; recommendation system; online competences certification; digital brick

## 1. Introduction

Enhancing the student's experience with online learning platforms is a goal of many educational institutions at any school or university level. Providing students with online materials, activities, courses and feedback can improve students' achievements and satisfaction even if the main part of the teaching is organized in traditional physical classrooms [1]. School and university closures caused by the COVID-19 pandemic have led all educational organizations to adopt online teaching and learning platforms, experiencing the advantages (and the barriers too) of online classes [2] to the point that many of them have decided to maintain e-Learning tools even after the recovery of in presence activities [3]. Among benefits, educational institutions appreciate in particular the potential of digital technologies to provide rapid feedback to students, supply continuous assessment environments, enable students to share educational achievements both through informal channels (for example, social networks) and formal certifications. As we know, assessment and evaluation have a central role to measure the level of transmission of knowledge and expertise to the student [4,5].

Concerning blockchain technology, we found five main areas of application for the education domain. (1) Certificate/degree verification: studies of how blockchain can assist institutions in validating student diplomas and can provide better control over how students earn certificates [6–8]. (2) Students' assessments and exams: automated mechanisms for the organization of exams and assessment schemes for students [9,10]. (3) Credit transfer: applications for storing student records and transcripts, and transferring credits between educational institutions [11,12]. (4) Data management: applications for connecting students' records across institutions as well as exchanging smart contracts for managing students' data [13,14]. (5) Admissions: applications for facilitating students in providing documents when applying to universities [15,16]. Beyond clear benefits, researchers are facing a number of problems in exploiting blockchain technology for education, the most important for our purpose concern the usability (the terminology is often unclear and the user may have to deal with several complicated settings) [6,8], the immutability (that is a challenge for some processes, such as diploma revocation) [12], and the scalability (increasing the number of participants as educational institutions, students, market players) [14,15].

Open Badges are fundamentally digital entities that can be earned both online and offline, and that indicate the learner's achievements (formal and informal), providing information about the issuing institution [17]. Badges are created, issued and managed through an open-source system, named Open Badge Infrastructure, conceived by the Mozilla Foundation and currently maintained by the IMS Global Learning Consortium [18]. Despite an initial increasing adoption, however, critics have raised many objections as the lack of shared meaning of digital badges [19], their role in the commodification of learning [20], the theory of motivation displacement [21], and other concerns about credibility, reliability and privacy [22]. Attempting to overcome these issues, in particular the lack of content standardization, systematic and shared approach, credibility, reliability, and privacy that are key properties for issuing formal certifications, in the last years, researchers started to integrate digital badges with blockchain Refs. [23–25]. Nevertheless, agile, usable and reusable applications still are in their infancy. No general software frameworks are available for institutional organizations.

Regarding machine learning, in recent years there has been a clear progressive trend toward applying it to foster personalized learning and precision education [26]. The newest mapping study of using machine learning approaches for precision education [27] showed us that the major part of modern research focuses on defining new artificial intelligence methods (i) to make predictions of the student performance, (ii) to profile the student's behavior and to cluster learning styles, and (iii) to provide recommendations to students of appropriate learning contents for their profiles. Particularly important for our research purposes is the study of recommendation algorithms for e-Learning to supply personalized learning objects to students that want to earn digital badges and certifications. In literature, we found four types of recommendation systems known as (i) Content-Based, (ii) Collaborative Filtering, (iii) Knowledge-Based, and (iv) Hybrid Systems [28]. The hybrid strategies are those that can deliver better recommendations especially if coupled with appropriate machine learning and deep learning methods for data filtering [29].

The research we briefly cited before, provided us with a strong scientific ground, and, at the same time, showed us the need to invest more effort on delivering open and flexible online environments to help students in finding and passing courses with final formal certifications of learning. In other words, the research gap we intended to fill, is to provide an intelligent framework that innovates the way students can obtain and share formal certifications of learning they earn during studies, enhancing the student's experience and preserving, at the same time, security, transparency and openness to link administrative processes. Trying to give our contribution to improve the state of the art in a research domain we already faced in the past [30,31], we evolved an existing commercial e-Learning platform named Digital Brick (learning.digitalbrick.it, in Italian), coming to a novel one specifically designed to enhance the students' experience in obtaining formal certifications

of their competences. We put our conceptual and experimental effort following two orthogonal directions: on the one side, we exploited digital badges and blockchain as first-order entities that enable organizations to share recognized achievements among earners and issuers. On the other side, we defined new machine learning algorithms to provide students with personalized recommendations of online learning content, online courses and learning paths that are more suitable for their profiles and learning styles. In other words, we worked around two research questions associated to the research gap:

RQ1. It is possible to connect open badges, social networks and blockchain to share formal certifications of learning, having a minimum impact both on the student's digital habitat and on the administrative information systems of educational institutions?

RQ2. It is possible to define new recommendation models to give students the personalized guidance they need on online learning materials, suggesting them learning paths useful to earn formal certifications?

We started our work by conducting a deep study of the state of the art addressing two related topics: (i) the use of blockchain technology and open badges for education credit transfer, and (ii) existing machine learning models for personalized education to guide students in the learning material more useful to study for earning credits and related certifications. To obtain a reusable approach, we designed a novel system architecture around a SCORM compliant learning management system. We added a specific module to provide services for the definition and issuing of formal certifications using digital badges according to the IMS Open Badges standard. We introduced a separate module exploiting blockchain technology to make the sharing of badges among actors more secure, transparent and open. Finally, we designed a complete recommendation algorithm based on a pipeline of different machine learning techniques (clustering, singular value decomposition, reinforced learning) to give advice to students about study materials and learning paths they have to follow to prepare themselves to obtain certifications.

The rest of the paper is organized as follows: Section 2 provides the reader with all the details of how we conducted our study, in particular the design of the system architecture focusing on Certification and Recommendation modules, and the machine learning algorithms we defined. Section 3 reports on quantitative results of the Digital Brick usage through a laboratory case study that involves all the components of the architecture. Section 4 analyzes the results, discusses their implications, and presents research limitations. Finally, Section 5 summarizes our key messages, sketching future research directions too.

## 2. Materials and Methods

### 2.1. Digital Brick Software Architecture

In Figure 1 we provide readers with a high-level view of the software architecture for the Digital Brick system. In particular, the figure represents the actors (user categories) and the three main functional components. Among the actors, the Student is interested in earning digital badges and certifications, which are issued by an Educational Institution that provides online courses authored by Teachers. Digital badges and certifications are accessed by Viewers, for example companies that look for new talents to hire. The central component of Figure 1 is a SCORM compliant Learning Management System—of which the main modules are depicted—that provides learning assets, learning objects and courses stored in a repository. The LMS collaborates on the one hand with the Certification System to issue open badges and certifications validated through a blockchain, on the other hand with a machine learning enabled Recommendation System to suggest to students personalized learning contents, learning objects, and learning paths.
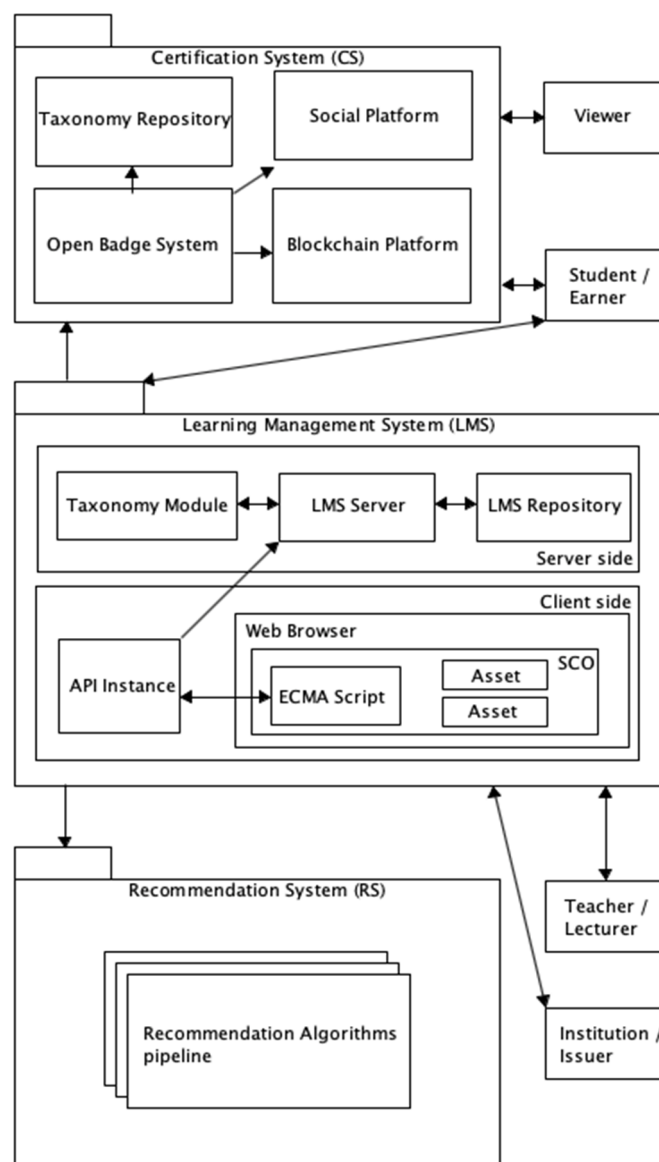
**Figure 1.** Digital Brick software architecture.

## 2.2. The Certification Sub-System

The Certification System (CS) is accessed by digital badge and certification issuers (Educational Institutions) through the LMS, as well as by Students interested in interacting with Viewers that are looking for new competences. As Figure 1 shows, digital badges and certifications meta-data are organized through a Taxonomy Repository to use a hierarchical set of well-defined keywords that make the research operations of Viewer easier to be accomplished. An Open Badge System gives the possibility to Educational Institutions to store the hash of issued digital badges in a Blockchain Platform adding transparency and security features, and enables Students to publish earned badges in social spaces. Typically, blockchains and social networks are released adopting third party tools. For this reason, the CS we have designed for the Digital Brick architecture contains just proxies to make simple the communication with the LMS. In Figure 2, we provide readers with internal details of the Open Badge System. A Mozilla Badgr repository gives users complete control over their achievements and data, so they can be organized in an e-Portfolio module being certain of the compliancy with the IMS Open Badges standard.
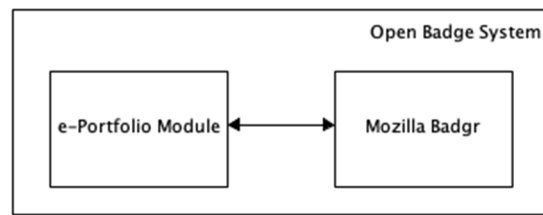
**Figure 2.** Open Badge System components.

### 2.3. The Recommendation Sub-System

The Recommendation System (RS) collaborates with the LMS proposing to Students learning contents to study to earn desired certifications. We decided to provide the RS of the Digital Brick platform with a hybrid architecture, coupling collaborative filtering with content-based filtering, because this combination enable us avoiding well-known problems as "cold-start" and "data sparsity" [32].

Figure 3 shows the internal architecture of the RS. The RS takes as input from the LMS the Learning Style vectors for each enrolled student, encoded adopting the Felder-Silverman Learning Style Model [33], and the Student-Item Rating Matrix, which stores the rating each student assigned to every learning item he/she evaluated. The RS generates as output for the LMS a list of top-N recommended learning items (a different list for each student). To produce this list, the RS exploits three different collaborative filtering algorithms (AROLS, Cosine Similarity and Pearson Correlation, Matrix Factorization through Singular Value Decomposition), hybridized with a content-based filtering algorithm thanks to three Hybridization Modules. A Recommendation Selection Module compares filtered recommendations and outputs the N most recommended items. Figure 4 provides readers with the pseudo-code of the collaborative filtering algorithm with the Felder-Silverman approach we adopted. Figure 5 shows the content-based algorithm that exploits the Cosine Similarity and Pearson Correlation coefficient approaches we implemented.
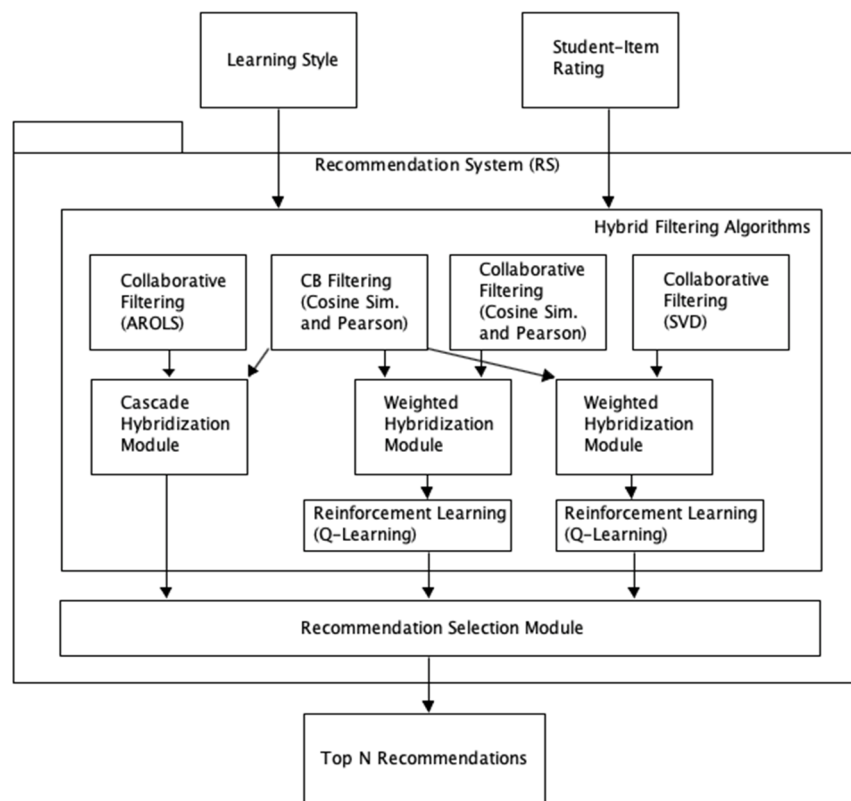


**Figure 3.** Recommendation System components.

**Input**: LS (Learning Style) and Student-Item Rating Matrix;
LS := learning style vector for the current student;
Cluster the student learning style applying K-Means;
cs := nearest cluster to LS computed by cosine similarity $c(x, y) = \frac{x \cdot y}{\|x\| \cdot \|y\|}$;
**foreach** $x \in LO$ **do**
    I := set of top-n nearest elements to LS in cs that have rated x computed by
    Pearson Correlation $P(x, y) = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}$;
    **if** $\|I\| > 0$ **then**
        Calculate the predicted rate for x as $\overline{r_1}(LS, x) = \frac{\sum_{s \in I} P(LS,s) \times r(s,x)}{\sum_{s \in I} P(LS,s)}$;
    **end**
    **if** $\|I\| = 0$ **then**
        Calculate the predicted rate for x as $\overline{r_2}(LS, x) = int(0.5 + P(LS, x) \times 5)$;
    **end**
**end**
Insert the obtained predicted ratings in the Prediction Matrix P;
**Output**: Prediction Matrix P;

**Figure 4.** Collaborative Filtering with Felder-Silverman approach.

**Input**: LS (Learning Style) and Student-Item Rating Matrix;
LS := learning style vector for the current student;
O := set of all learning objects (LO) rated by LS;
**if** $O \neq \varnothing$ **then**
    Cluster O applying K-Means;
    **foreach** $x \in LO$ **do**
        $co_x$ := nearest cluster to x computed by cosine similarity $c(x, y) = \frac{x \cdot y}{\|x\| \cdot \|y\|}$;
        J := set of top-n nearest elements to x in $co_x$ computed by Pearson Correlation
        as $P(x, y) = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}}$;
        Calculate the predicted rate for x as $\overline{r_3}(LS, x) = \frac{\sum_{s \in J} P(x,s) \times r(LS,s)}{\sum_{s \in J} P(x,s)}$;
    **end**
**else**
    Cluster all LOs applying K-Means;
    co := nearest cluster to LS;
    **foreach** $x \in co$ **do**
        Calculate the predicted rate for x as $\overline{r_2}(LS, x) = int(0.5 + P(LS, x) \times 5)$;
    **end**
**end**
Insert the obtained predicted ratings in the Prediction Matrix P;
**Output**: Prediction Matrix P;

**Figure 5.** Content-Based Filtering with Cosine Similarity and Pearson Correlation approach.

The AROLS—Adaptive Recommendation based on Online Learning Style—collaborative filtering algorithm [34] generates recommendations applying sequentially three steps: (i) clustering students according to their learning styles using K-Means; (ii) for each cluster, filtering the learning items using the Cosine Similarity; and (iii) grouping the learning items with the Apriori Association Rule algorithm [29] according to the preference level of students. The Matrix Factorization based collaborative filtering algorithm exploits the Singular Value Decomposition (SVD) technique, which is a matrix factorization method used in linear algebra for the decomposition of matrices that enable transforming a space of interactions into a space of latent values [35].

We decided to take into account that the ratings students assign to learning items can evolve over the time due to the "contrast effect": a student can evaluate the same item differently depending on what he/she studied before. As Figure 3 shows, in cascade to collaborative filtering with Cosine Similarity and Pearson Correlation, and with Matrix Factorization, we put a Reinforcement Learning (RL) module. RL is a machine learning technique that aims at training agents to choose actions from their action space in order to maximize the rewards over time [36]. One of the most popular RL algorithms is known as Q-Learning, which implements a temporal difference learning strategy.

It is possible to formalize the collaborative filtering problem as a Markov decision-making process (MDP) and to optimize the predictions learning form the sequence of contents a student evaluated over the time using the Q-Learning algorithm. Figure 6 provides readers with the pseudo-code of the Q-Learning algorithm. To the best of our knowledge, this is the first time a RL method is applied to collaborative filtering of learning contents in the education domain.

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**Input**:   α: learning rate; γ: discount factor;
        T$_i$: number of items rated by student i;
        X: Student-Item Rating matrix;
        P: Prediction Matrix;
$\forall s \in S, \forall a \in A$ set Q(s, a) := 0;
Convert $X \in \mathbb{R}^{N \times M}$ to sequence of ratings;
**foreach** student i form 1 to N **do**
    **foreach** item j form 1 to T$_i$ **do**
        Calculate the reward as $r\left(s_j^{(i)}, a_j^{(i)}\right) = s_{j+2}^{(i)} - predictor(i, j)$;
        Update the Q-function Q(s, a) using the Bellman equation
           $Q(a, s) = Q(s, a) + \alpha[r(s, a) + max_{a'}Q(\delta(s, a), a') - Q(s, a)]$
    **end**
**end**
**Output**: Q(s, a) the estimated sum of reward;

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**Figure 6.** Q-Learning algorithm (training phase).

Readers can verify that from a theoretical perspective, the Digital Brick software architecture responds to Sustainable Development Goals (SDGs), which are part of the Agenda 2030 [37]. In particular, SDG number 4 aims to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all", is promoted by broad use of digital technologies (that are inclusive), thanks to blockchain that makes more secure, transparent and open the sharing of competences, and thanks to open badges and social platforms that enable all students to share their achievements without space and time limits; this correlation to SDGs is particularly significant to give adequate support to educational processes after the COVID-19 pandemic where, as we stated in the introduction section, the digital economic education use has increased exponentially. Students often get lost in the learning contents' hyperspace; they need tools to have active guidance, as well as open platforms to share their achievements.

## 3. Case Study and Results

The system test was done in vitro by executing both a functional and performance validation, operating on the CS and the RS separately. Regarding the CS, a private Ethereum software blockchain has been instantiated as a network of Docker software containers (see Figure 7) deploying smart contracts that represent target digital badges. The Bootstrap node creates the whole blockchain, while the NetStats node collects usage statistics. The Education Institution nodes send transactions (i.e., issue digital badges) or perform mining. All custom business logic has been developed using Java and JavaScript programming languages. Concerning the RS, the OULAD—Open University Learning Analytics Dataset [38] has been exploited to extract performance metrics about the machine learning implemented algorithms. OLAUD contains information on 22 learning modules, 20 different types of learning activities, and 32,593 students with their assessment results (10,655,280 records). All machine learning algorithms have been developed using the Python v. 3.9.0 programming language, the Jupyter Notebook online development environment, and exploiting the Numpy (for scientific computing), Pandas (for matrix computing), Sklearn (for supervised and unsupervised learning), SciPy (for statistics and linear algebra), Matplotlib (for data plot), and Seaborn (for data visualization) open-source Python standard libraries. The functions provided by the listed libraries gave us the possibility to calculate and plot the Mean Absolute Error and the Root Mean Square Error statistical measures to evaluate the quality of our algorithms.
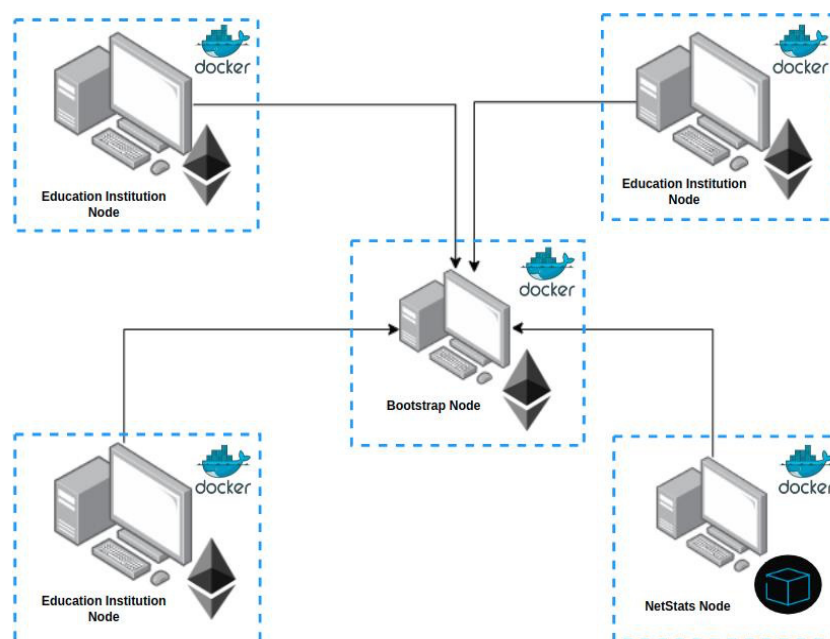
**Figure 7.** The certification Ethereum blockchain.

*3.1. Supported Use Cases*

The prototype of CS we developed, supports two main use cases: (i) open badge issuing from an educational institution to a student to certify credits he/she obtained, and (ii) open badge/certification verification by a third-party entity. Figure 8 shows screenshots of the whole process: on the top-left, an educational institution fills a form to generate the badge and sends it as a smart contract to the Ethereum blockchain. On the top-right, a student receives a new badge in his/her personal e-portfolio. On bottom-left, the Ethereum blockchain activity needed to verify an open badge is shown. Finally, on the bottom-right, a third-party entity interested in the certification verifies the corresponding badge. Figure 9 provides readers with a model (expressed in BPMN notation) of the certificate issuing process. The diagram shows the connections in the work of the platform systemically and describes the tasks and the relation among actors from the point of view of the educational flow. The diagram is self-explanatory: the flow starts from the top when a Student does an exam; the exam is verified by a Teacher that sends the results to the system. If the exam is passed, the Institution's Administration transfers a corresponding certification to the blockchain that, following the consensus algorithm, reaches a common agreement and confirms the certificate. At this point, the Student can share the certificate as an open badge through the social platform. A similar diagram (but trivial because just two actors are involved, the Student and the Recommendation System) can be established for the recommendation process. Thanks to the Digital Brick architecture, the prototype of RS, instead, supports all the use cases included in Figure 10 using the UML notation. In particular, the "Learning Object/Learning Content Recommendation" and the "Learning Path Recommendation" algorithms are those that have been implemented by exploiting the Jupiter Notebook environment and the Python language with the NumPy, SciPy, Scikit-learn, and Pandas open-source libraries.
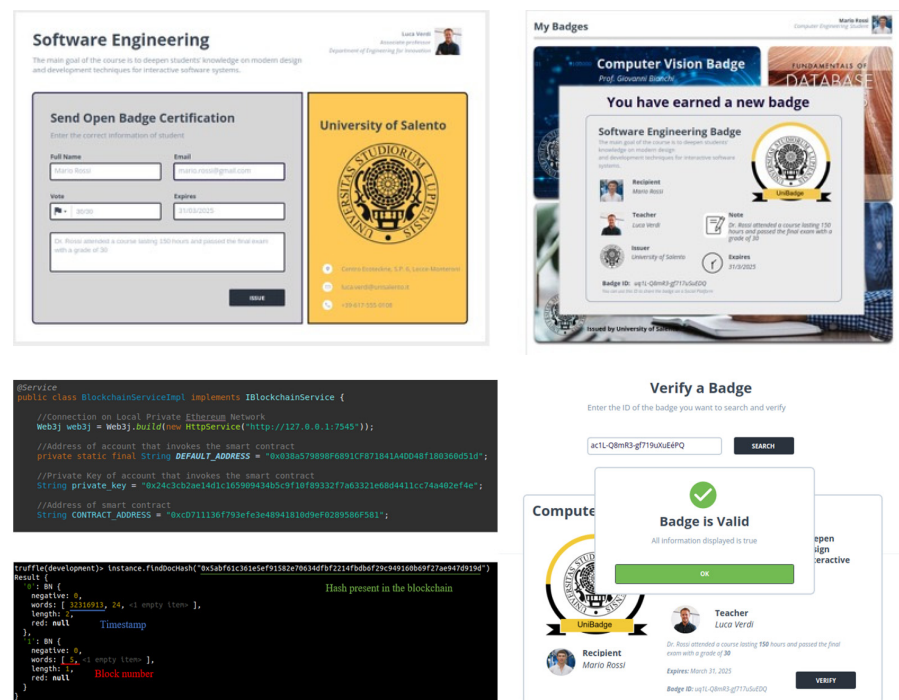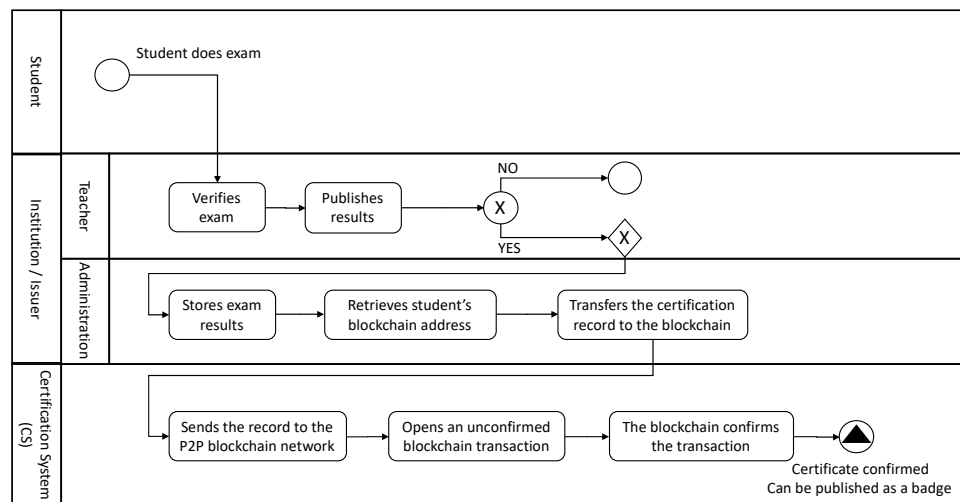
**Figure 8.** Certification use cases.



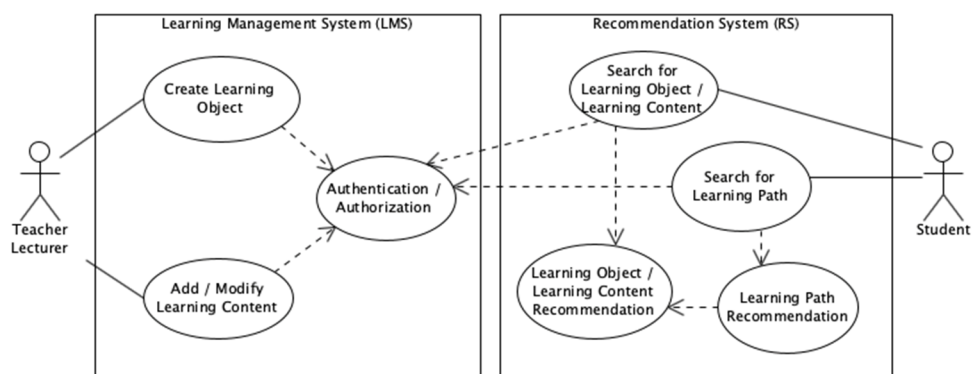**Figure 9.** Certification process.



**Figure 10.** Recommendation use cases.

*3.2. Quantitative Results for Certifications*

Quantitative results for the CS have been extracted by performing a stress test of the Ethereum blockchain as depicted in Figure 7 (SUT—System Under Test). To verify the ability of the SUT to perform correctly issuing and verifying certifications, as reported in Figure 11 we defined a representative workload for blockchain in three different configurations (1 miner node and 10 actor nodes, 2 miners and 10 actor nodes, 3 miners and 10 actor nodes), with an increasing number of transactions (i.e., certifications issuing or verification), or with an increasing rate of transactions. Using the Hyperledger Caliper blockchain benchmark tool, we measured the transaction latency and the transaction throughput. The transaction latency $L = tc - td$ is defined as the difference between the transaction completion time (the moment in which a transaction is confirmed by blockchain) and the transaction deployment time (the moment in which a certification has been issued or verified). Whereas the transaction throughput $Th$ = the number of committed transaction (tx)/total time (s) is defined as the number of successful transactions per second starting from the first transaction deployment time. Figure 12 provides readers with quantitative results for latency (top) and throughput (bottom) referred to the certification issuing use case at an increasing number of transactions. For lack of space, we do not report similar results for the certification verification use case and at an increasing transaction rate. On the top left and bottom left of Figure 12, Ethereum results (dashed line) are compared to the state-of-the-art (solid line) represented by the Hyperledger Fabric system [39].

| SUT configuration | | | Transaction type | Workload | |
|---|---|---|---|---|---|
| | | | | sendRate (TPS) | Transaction (TX) |
| 1 Miner and 10 Nodes | 2 Miners and 10 Nodes | 3 Miners and 10 Nodes | saveHash (Certificate Issuing to Student) | Constant send rate | |
| | | | | 100 | 1 |
| | | | | 100 | 10 |
| | | | | 100 | 100 |
| | | | | 100 | 1,000 |
| | | | | 100 | 10,000 |
| | | | | Constant number of transactions | |
| | | | | 10 | 1,000 |
| | | | | 100 | 1,000 |
| | | | | 1,000 | 1,000 |
| | | | findHash (Certification validation) | Constant send rate | |
| | | | | 100 | 1 |
| | | | | 100 | 10 |
| | | | | 100 | 100 |
| | | | | 100 | 1,000 |
| | | | | 100 | 10,000 |
| | | | | Constant number of transactions | |
| | | | | 10 | 1,000 |
| | | | | 100 | 1,000 |
| | | | | 1,000 | 1,000 |

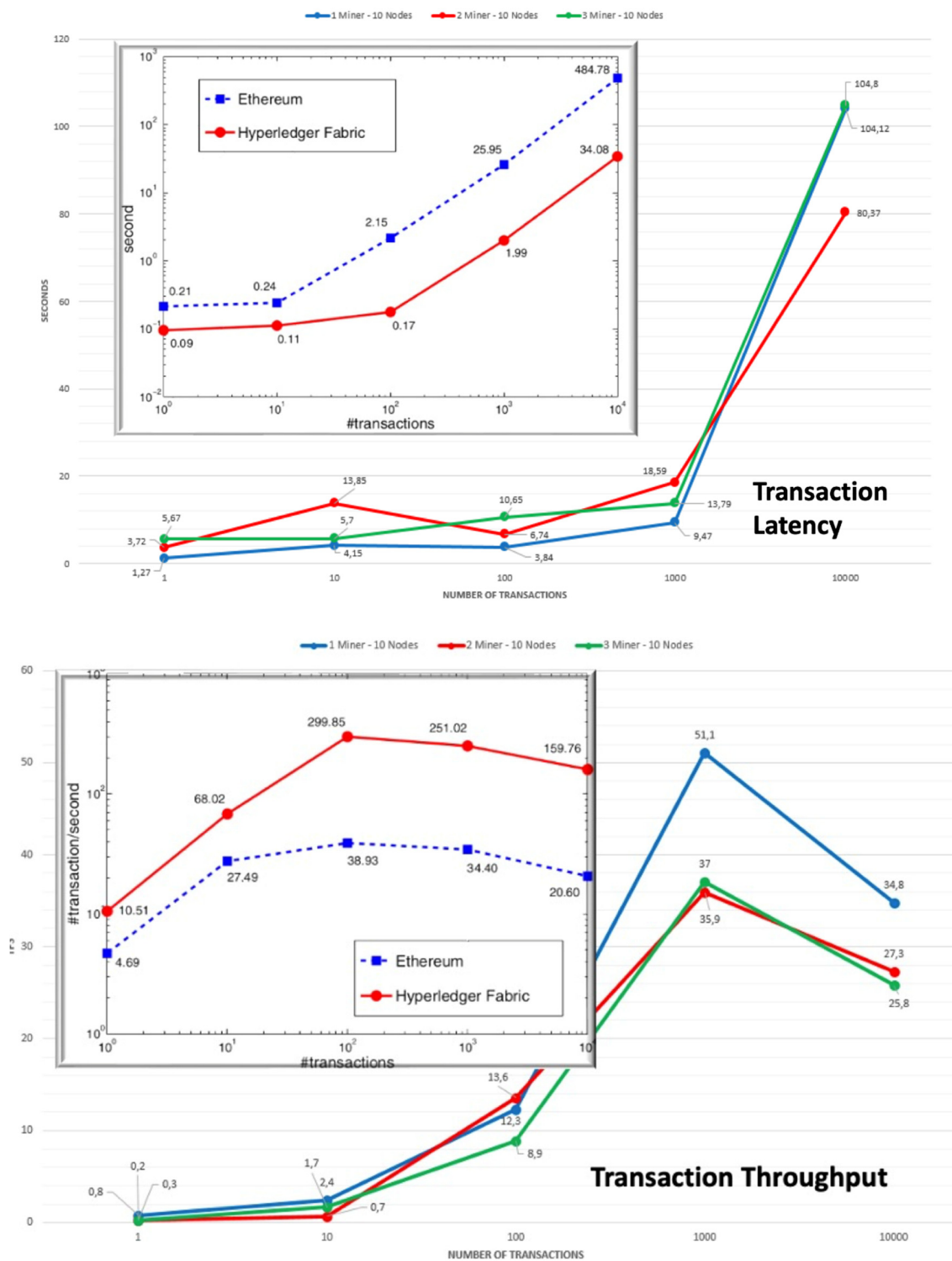**Figure 11.** CS quantitative test configurations.

**Figure 12.** Quantitative results for the CS.

### 3.3. Quantitative Results for Recommendations

To test the prototype of RS we deployed, we considered four different scenarios supported by the OULAD dataset, consistently with the recommendation use cases represented in Figure 10: (i) 15 students and 15 learning objects randomly selected from the dataset to test the content recommendation performances, (ii) 50 students and 50 learning objects, (iii) selection of students for which the dataset does not contain past evaluations to test the cold start problem, and (iv) selection of learning objects for which the dataset does

not contain interactions at all (i.e., never accessed by anyone). The scenarios were named, respectively, "15 predictions", "50 predictions", "cold students", and "cold LOs".

For each scenario, we extracted quantitative indicators to evaluate the accuracy of predictions obtained by the machine learning algorithms we implemented. In particular, we calculated the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE).

$$MAE = \frac{\sum_{i=1}^{n} |r_i - \hat{r}_i|}{n} \quad RMSE = \sqrt{\frac{\sum_{i=1}^{n} (r_i - \hat{r}_i)^2}{n}} \tag{1}$$

Figure 13 reports MAE and RMSE measures we collected during our tests. Starting from the top of Figure 13, the first histogram contains MAE values for (i) the content-based filtering algorithm, (ii) the collaborative filtering algorithm, and (iii) the hybrid filtering algorithm, respectively, referred to the four scenarios. The second image (middle) contains RMSE values for the same algorithms. In the third histogram (bottom), we present three series of MAE values for recommendations done using different dimensions of student-item rating matrices ($15 \times 15$, $15 \times 10$, $15 \times 5$). The fourth bar of each sequence is referred to the reinforcement learning Q-Learning algorithm (QL).
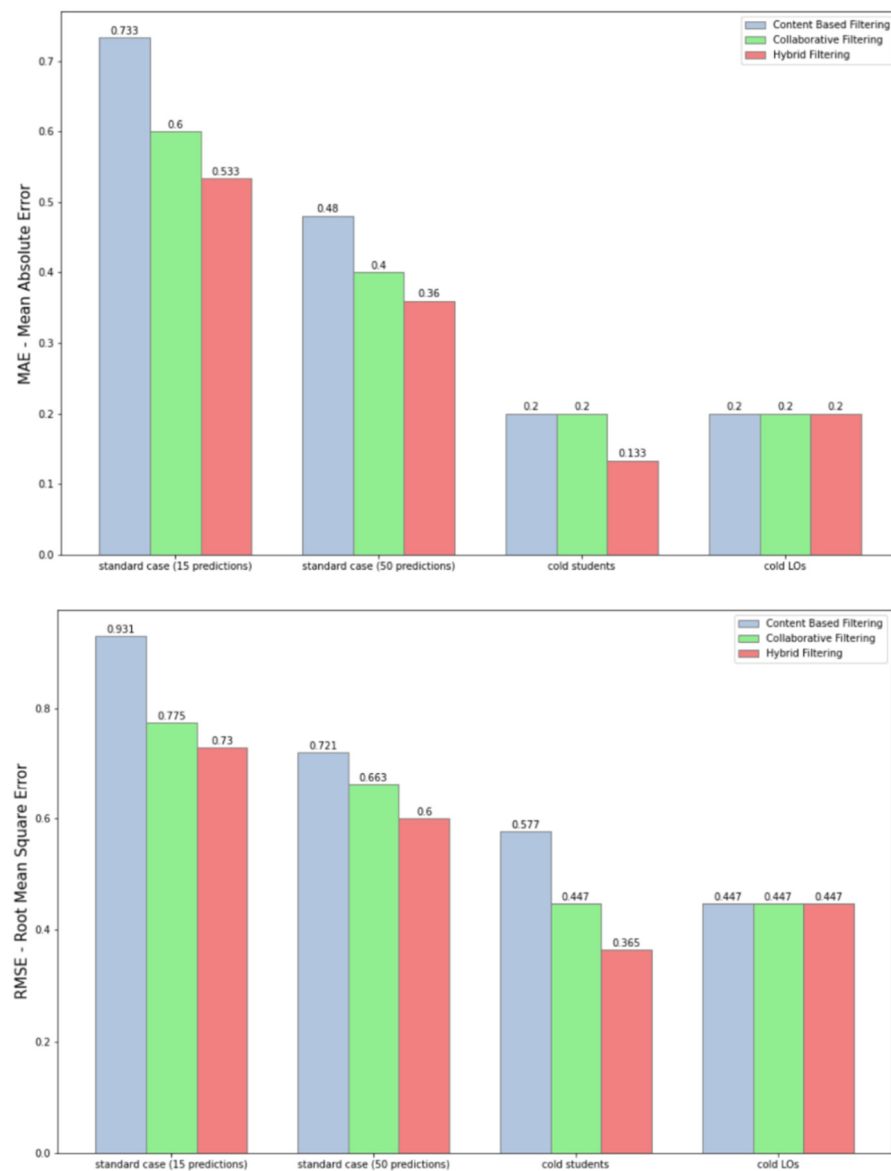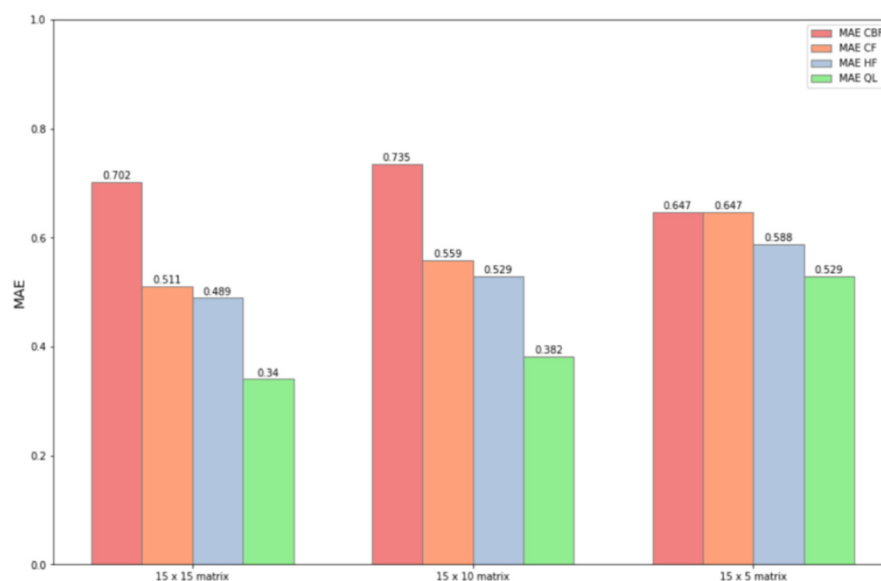




**Figure 13.** *Cont.*

**Figure 13.** Quantitative results for the RS.

## 4. Discussion

The discussion of functional and quantitative results for the CS and the RS are provided separately in this section.

### 4.1. Discussion of Results for Certifications

Compared to the state of the art on the adoption of blockchain technology for education, we briefly presented in Section 1, to the best of our knowledge, this is the first time that Ethereum technology has been exploited for credits and a knowledge certification; it is also the first scientific experiment aiming to integrate the Ethereum blockchain technology with the Open Badge platform according to the IMS standard to make the process of students achievements sharing among actors more secure, transparent and open.

We chose to use the Ethereum blockchain technology because it is supported by a large community of users and developers. For this reason, a significant base of tools, reports, white papers, technical documents, and project experiences is available, making simpler the deployment of new systems; however, the effort of engineers on Ethereum is totally focused on developing digital currency and smart contracts exchange applications for different business domains as fintech, logistics, energy, food, etc. With our work, we filled a gap in the education domain.

The quality work of researchers in Refs. [11,12], we referred to as a scientific baseline in our effort, uses the ARK blockchain to exchange student records and transcripts among educational institutions. The ARK blockchain is less widespread than Ethereum making it harder and risky the adoption by educational institutions. But above all, the ARK blockchain uses the Delegate Proof of Stake (DPoS) consensus algorithm (i.e., the procedure through which all the peers of the blockchain network reach a common agreement about the present state of the distributed ledger, in our case the present state of issued certifications) while the Ethereum blockchain adopts the Proof of Work (PoW). Compared to PoW, DPoS is more centralized as it delegates to a few nodes to validate transactions (i.e., certifications and digital badges issuing requests). Consequently, the fewer actors are in charge of keeping the network active, the easier it is to gain whole control of the distributed ledger. In our opinion, this is a risk for the educational domain because of the centrality of qualities such as openness, democracy, inclusivity, and equitability, as SDG number 4 recalls.

Focusing on quantitative results obtained during the performance assessment of CS, as Figure 12 shows, we achieved a better indicator in terms of transaction latency and transaction throughput than the Ethereum single node blockchain as reported in Ref. [40] we compared our solution with. As an example, for a number of transactions of 103, the

transaction latency of our solution is better than Ethereum single node by 61.96% with one miner node and by 28.36% with two miner nodes, respectively. In the same configuration, the transaction throughput is better by 48.54% (one miner node) and by 4.36% (two miner nodes). We also measured that the CS we deployed is able to handle a higher maximum number of concurrent transactions than the Hyperledger Fabric node discussed in Ref. [40], but lower than the Ethereum node (the Hyperledger Fabric is an implementation of a private blockchain technology that is intended as a foundation for developing blockchain applications for a wide variety of industry [41]). In fact, our CS is able to process a maximum of 27,732 concurrent transactions compared to 20,000 maximum concurrent transactions of the Hyperledger Fabric and 50,000 maximum concurrent transactions of the Ethereum blockchain; however, although the maximum number of concurrent transactions can be a critical parameter in the financial domain to exchange cryptocurrency, it is not in the educational sector.

## 4.2. Discussion of Results for Recommendations

The first and the second histogram chart starting from the top of Figure 13 show us that the diverse algorithms we implemented have different accuracy performances in predicting learning contents and learning paths to recommend to students. In particular, moving from content-based filtering (CB) to collaborative filtering (CF), in general the accuracy increases as both MAE and RMSE decrease. Combining CB and CF with the hybrid filtering (HF) strategy, we obtained better performances in all test scenarios we considered. For this reason, our machine learning architecture includes hybridization modules (see Figure 3).

As the third chart in Figure 13 demonstrates, inserting in cascade to HF a reinforcement learning Q-Learning algorithm (QL) allowed us to achieve superior accuracy in our recommendations. Even if mixtures of heterogeneous machine learning algorithms are not a scientific novelty at all, to the best of our knowledge, this is the first time a Q-Learning scheme is applied in the educational domain to recommend content and learning paths to students fostering their learning achievements and certifications.

To be more precise, using QL we obtained an improvement of the MAE index by 10% for a $15 \times 5$ student-item rating matrix, by 27.7% for a $15 \times 10$ matrix, and by 30.2% for a $15 \times 15$ matrix. In relation to the RMSE, the percentages of improvement we measured have been by 5%, 10%, and 16.8%, respectively. We plot the accuracy improvements due to the Q-Learning algorithm in Figure 14.



**Figure 14.** Accuracy improvement due to QL.

As we reported in Section 1, other researchers did extensive experimental works applying machine learning and deep learning techniques with the aim to propose learning objects to students in order they reach their study goals keeping into account learning profiles [26–29,42]. Among these studies, authors in Ref. [42] proposed a recommender algorithm that suggests personalized learning objects based on the student learning styles.

If compared to this work, we obtained better prediction accuracy in terms of MAE and RMSE for CB, CF, and HF blocks. In detail, MAE values for CB, CF and HF, respectively, declared by authors in Ref. [42] are 1.52, 1.18, and 0.60, whereas we obtained 0.73, 0.60, and 0.53. Similarly, RMSE values for CB, CF and HF, respectively, declared by authors in Ref. [42] are 1.70, 1.60, and 0.85, whereas we obtained 0.93, 0.77, and 0.73. Researchers in Ref. [42], moreover, did not involve in their implementation of a reinforcement learning strategy.

### 4.3. Research Limitations

This work presents three limitations, one relevant both for the CS and the RS, and one specific for each sub-system.

The experimental validation of the Digital Brick framework (intended as the composition of models, algorithms and connections) has been done in vitro. In particular, for the RS we trained and gathered machine learning performance metrics of the algorithms using the OULAD dataset. Even if this dataset is adequately big (10,655,280 records) and realistic, we have to test the framework using data coming from students' online interactions with the Digital Brick system.

Concerning the CS, all performance metrics we presented in Section 3.2 are gathered by executing the SUT on a single hardware machine, virtualizing all the necessary nodes as represented in Figure 7. We expect that by deploying the CS on cloud architecture, the overall performance will increase.

Finally concerning the RS, as stated in Ref. [38] the OULAD dataset is not specifically designed for training and testing purposes of educational content recommendation algorithms. In fact, many records lack explicit student evaluation of referred learning contents. Nevertheless, the OULAD was the best choice to enable us to compare our work with the scientific state of the art.

### 5. Conclusions

As educational organizations plan to keep active online teaching and learning platforms even after the recovery of presence activities because of the COVID-19 pandemic, is crucial to enhance the students' experience in obtaining credits and formal certifications of their competencies.

In this paper, we presented the Digital Brick platform built around a standard SCORM-compliant learning management system that provides all actors involved in the learning field with an open certification system exploiting blockchain and open badge technologies. In this way, the sharing of certifications among actors becomes more secure, transparent and open, and at the same time students experience automatic guidance tools through learning materials and learning paths; this first part of the research work we designed in Section 2.2, we validated in Section 3.2, and we discussed in Section 4.1, is our explicit answer to RQ1; moreover, in this paper we presented a novel machine learning enabled recommendation system; this second part of the research work we designed in Section 2.3, we validated in Section 3.3, and we discussed in Section 4.2, is our explicit answer to RQ2. To the best of our knowledge, this is the first time an Ethereum blockchain and a reinforcement learning scheme are applied to education evolving the process of certification of competencies. Our quantitative results showed that for the CS we achieved better transaction latency and transaction throughput than the Ethereum single node blockchain as reported in the state of the art. For the RS, as well, we obtained better prediction accuracy in measuring MAE and RMSE indexes. These results fill the research gap we identified and explicitly expressed in the introduction section of this article.

We know that educational institutions may have some resistance and caution to introducing blockchain technology in their information systems, given the fluctuation of cryptocurrencies observed in recent years; however, in this work, we proposed the use of blockchain as a distributed ledger to share credits certifications and open badges. From a market point of view, the Gartner group expects that the business generated by blockchain applications will exceed USD 10 billion in 2022 [43], pulled by the needs of the Internet

of Things and smart contracts (like certifications) in market segments as logistics, energy, food, and agriculture; this should reassure educational institutions, which can find in the market a big number of blockchain operators, experts and cloud platforms. At the same time, it could be for the educational institution the opportunity to provide their information systems with a modern payment interface able to accept cryptocurrencies; moreover, a recent bibliometric analysis of blockchain technology research [44] reveals that blockchain fosters sustainability, i.e., it contributes to join the SDGs.

As a future step, we are organizing in vivo experiments engaging classrooms of Italian secondary schools and ITSs (Higher Technical Institute), offering them learning contents and certifications for ICDL digital skills on the topics of Industry 4.0. The involvement in the research group of Webscience Srl company, technical partner of AICA for ICDL (www.icdl.it), gives us the possibility to engage more than 2000 students during the experimental phase of the Digital Brick project planned for September 2022.

**Author Contributions:** L.M. and R.P. formulated the idea, identified the research requirements and objectives, and defined the system architecture. M.P. and M.Q. developed algorithms and proof-of-concepts. M.P., M.Q. and E.D. carried out the functional validation of the proposed solution. All authors prepared and critically edited the manuscript. All authors have read and agreed to the published version of the manuscript.

**Data Availability Statement:** The data presented in this study will available in https://webscience.it/en/ at the end of the Digital Brick project.

**Conflicts of Interest:** The authors declare no conflict of interest.

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