Towards Serendipitous Learning Resource Recommendation

Sahar Sayahi[1], Leila Ghorbel[1], Corinne Amel Zayani[1] and Ronan Champagnat[2]
[1]*MIRACL Laboratory, Sfax University, Tunis Road Km 10 BP.242, Sfax, 3021, Tunisia*
[2]*L3i Laboratory, La Rochelle University, Avenue Michel Crépeau, La Rochelle, 17042, France*

Keywords: Online Learning, Recommender System, Filter Bubble, Educational Dataset, Data Mining, Serendipity Dimensions.

Abstract: Since the outbreak of the pandemic, online learning has become widely applied. Indeed, learners follow Learning Resources (LR) available on different platforms. Therefore, it's very difficult for learners to choose LR that matches their needs. They may face disorientation and cognitive overload problems. In fact, multiple studies have been conducted on Recommender Systems (RS) in order to provide learners with the best LR that correspond to their needs and complete their training. Unfortunately, these basic RS can lead to an overly restricted set of suggestions and inadvertently place learners in a so-called "filter bubble". The latter is resolved through serendipitous RS, which suggest to learners surprising LR based on serendipity dimensions such as unexpectedness, novelty and usefulness. In this research paper, we first present our serendipity-oriented recommendation architecture. Then, we enrich our collected educational dataset with the dimensions of serendipity. Finally, we evaluate the real learner's satisfaction on serendipitous LR's recommendation.

1 INTRODUCTION

Over the past few years, the need for online learning has increased, especially after the Coronavirus pandemic. During the lockdown period, online learning became a necessity in numerous countries to continue maintaining the educational process (Hermawan, 2021). This learning mode reinforces the importance of enhancing and developing online learning platforms in several forms: LMS (Learning Management System), LCMS (Learning Content Management System) or MOOC (Massive Open Online Courses) (Vora et al., 2020). These platforms provide an important number of available LR which can generate for learners certain problems of disorientation and cognitive overload (Dien et al., 2022).

RS have emerged as a solution to overcome these problems. They aim to satisfy the learner through suggesting the best LR to complete his/her training. In literature, there are three basic recommendation approaches (Kundu et al., 2021), namely content-based, collaborative filtering, and hybrid. These approaches suffer from the problems of cold start, sparsity and scalability. In order to overcome the above mentioned problems, advanced RS have emerged in a wide range of fields. These systems take into consideration real users' social relationships (Troudi et al., 2021) and use matrix factorisation and deep learning (Guo et al., 2019; Dien et al., 2022; Zhang et al., 2022). Departing from this review, we notified that the majority of basic and advanced RS focus on recommendations that are very close to the learner's profile. They always provide him/her with the same type and content of resources on the same subject and idea. This problem is called the filter bubble (Nguyen et al., 2014), which is resolved by serendipity-oriented RS. The latter suggest to learners surprising LR based on serendipity dimensions.

The most important problem of serendipitous RS is the lack of public available datasets for evaluation. In order to overcome this problem, we mainly tackle the basic principle and specify the steps of the construction of our dataset. The latter must contain dimensions explaining the serendipity of LR from the learner's perspective.

The rest of this paper is organized as follows. In section 2, some existing studies about recommender systems, serendipity, and educational datasets are presented and discussed. Then, in section 3.2, we give an overview of our approach. In section 4, we demonstrate the data processing. In section 5, we identify the applied algorithms to determine the serendipity dimensions. In section 6, we describe the evaluation results. Finally, section 7 concludes the paper and of-

Sayahi, S., Ghorbel, L., Zayani, C. and Champagnat, R.
Towards Serendipitous Learning Resource Recommendation.
DOI: 10.5220/0012059800003470
In *Proceedings of the 15th International Conference on Computer Supported Education (CSEDU 2023) - Volume 1*, pages 454-462
ISBN: 978-989-758-641-5; ISSN: 2184-5026

fers certain prospects for future works.

2 STATE OF THE ART

In this section, an overview about RS, serendipity and the faced challenges is displayed followed by a detailed synthesis.

2.1 Recommender Systems, Serendipity and Challenges

RS have emerged in online learning to enhance the quality of learning process and make it easier. They both help and motivate learners to more accurately learn and improve their academic performance through suggesting items (Learning resources: courses activities, videos, ...) that correspond to their needs (Fraihat and Shambour, 2015).
Based on an in-depth study, we inferred that RS (Dien et al., 2022; Guo et al., 2019; Troudi et al., 2021), in different fields including online learning, focus on items (courses, movies, jobs, etc.) that are very close to the user's (learner's) profile. In (Zhang et al., 2022; Guo et al., 2022), authors developed a session-based recommendation approach which takes into account the dependency between items and user's behaviour. These works aim to capture the sequential dependencies between items within the current session.
The above mentioned approaches always provide users with the same type and content of items having the same subject and idea. This problem is called the filter bubble (Nguyen et al., 2014; Pardos and Jiang, 2020) which is resolved by a serendipity-oriented RS. The latter helps the user find a surprisingly interesting item that he/she might not have otherwise discovered (or it would have been really hard to discover) (Kaminskas and Bridge, 2016; Pardos and Jiang, 2020).

Serendipity is a complicated and interesting concept for research. The major source of complexity and ambiguity of this concept resides in the fact that it is in association with emotion (Ziarani and Ravanmehr, 2021b). As a result, defining serendipity in RS is a challenging problem.

In order to properly interpret user's emotion towards items, there are several serendipity dimensions that are determined in different research studies (Kotkov et al., 2020; Ziarani and Ravanmehr, 2021b; Zhang et al., 2021). These dimensions can be measured in terms of item usefulness, novelty and unexpectedness. Items with these dimensions are very rare, making it hard to present serendipitous recommendations (Ziarani and Ravanmehr, 2021a; Li et al., 2019). For this reason, the majority of the research works that tackle the serendipity in recommendation have faced numerous challenges. Authors in (Ziarani and Ravanmehr, 2021b) stated different challenges, among which we can mention ambiguity in serendipity definition, methods for serendipity evaluation, emotional aspect and the lack of public datasets for serendipity.

In this paper, we address the two last challenges. The first concerns emotional aspects of serendipitous recommendations, which is always very subjective and imprecise, contributing to the difficulty of finding them. The second challenge relates to lack of public datasets for serendipity, and specially educational public datasets. In fact, the majority of available datasets that contain especially serendidpty label are related to movie recommendation[1]. Additionally, the avalability of general RS datasets such as MovieLens[2], OpenStreetMap[3] and Jester[4] help researchers perform works that deal with serendipitous recommendations .

In the current work, we are basically interested in online learning domain where research works are based on RS for Technology Enhanced Learning (TEL). From this perspective, before presenting the serendipity recommendation approaches, we have studied the most prominent datasets used in this domain for different purposes (Educational Data Mining, Process Mining, etc.).

2.2 Educational Datasets

In literature, there are three types of data sources that represent the public available datasets in educational domain (Mihaescu and Popescu, 2021). The first type consists of general-purpose repositories where educational datasets are uploaded such as UCI ML[5], Mendeley[6] and Harvard Dataverse[7] data repositories. The second type of Datasets used in competitions stands for a category that became very popular in the last years. These datasets are invested to speed up the comparative analysis of proposed solutions compared to the solution of other competitors. The third type corresponds to standalone datasets. The dataset maintenance, the proposed solution and the results are

[1]https://grouplens.org/datasets/serendipity-2018/
[2]https://grouplens.org/datasets/movielens/
[3]https://www.openstreetmap.org/map=6/33.971/9.562
[4]https://eigentaste.berkeley.edu/dataset/
[5]UCI Machine Learning Repository, https://archive.ics.uci.edu/ml/index.php
[6]Mendeley Data Repository, https://data.mendeley.com/
[7]Harvard Dataverse, https://dataverse.harvard.edu/

at the disposal of the author.

Data represented in these datasets are collected after the analysis of resources and learners' data in order to improve their learning experience and skills.

After checking the content of these datasets, we realized that they differ a lot in their structure, their recorded features which are useful uniquely for a specific purpose and their usefulness in terms of citations, practical uses and approaches. Furthermore, we notice that most of data are encrypted.

Although these datasets have been used for a long time and among the most referenced ones, we find it difficult to find some of them as they are cited but not publicly available. Consequently, we are unmotivated to use them in our work and even in our future academic research.

For this reason, we opted for elaborating our dataset.

Table 1 exhibits some educational datasets and their main features.

2.3 Synthesis

Owing to the importance of RS, various works have been developed in this context. However, in view of the complexity and variety of challenges, RS for online learning have not been yet well elaborated, where most researchers use basic RS. As far as our research is concerned, we seek to make serendipitous recommendations. Therefore, we discuss approaches that invest serendipity for RS. These approaches display various basic shortcomings.

The first shortcoming is related to the dimensions of serendipity in the recommendation (unexpectedness, novelty, usefulness, etc.) to achieve serendipity. We notice that some works are confused in terms of using one or two features (Ziarani and Ravanmehr, 2021a; Zhang et al., 2021; Li et al., 2019; Kaminskas and Bridge, 2016; Pardos and Jiang, 2020).

The second shortcoming resides in the fact that the majority of works that are concerned with serendipity do not take into account user's behavior and the emotional aspect (Ziarani and Ravanmehr, 2021a; Zhang et al., 2021; Kaminskas and Bridge, 2016).

Finally, it is noteworthy that almost all RS research studies are about movies or music (Ziarani and Ravanmehr, 2021a; Zhang et al., 2021; Li et al., 2019; Kaminskas and Bridge, 2016).

From this perspective, in order to overcome these limitations, we set forward our approach for LR recommendation based on serendipity dimensions. The basic merit of this approach lies in extracting a specific educational dataset and determining the dimensions of serendipity.

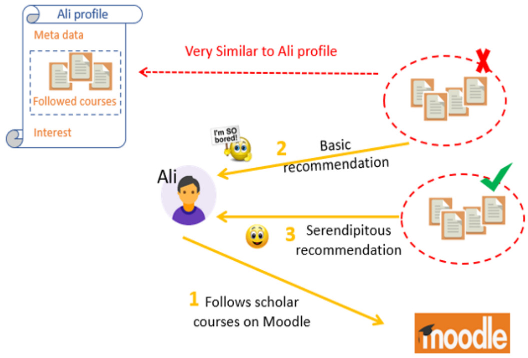

Figure 1: Motivated scenario.

3 OVERVIEW OF THE PROPOSED APPROACH

In order to introduce our proposed approach, we demonstrate the basic objectives to achieve serendipitous LR recommendation by a scenario in section 3.1. Then, we identify the proposed architecture in section 3.2.

3.1 Motivating Scenario

In this part, we exhibit a motivating scenario to clarify the basic purpose of the proposed approach that relates to the importance of serendipity-oriented recommender systems for online learning. In figure 1, We consider a student "Ali" who wants to accumulate knowledge and skills associated with his interests. Therefore, at the first step, he subscribes to the Moodle Learning Management System (LMS) provided by his school. Then, he follows the existing courses in Moodle delivered by his teachers (1). In order to enhance the education level, researchers include a basic recommender system based to the learner preference (2). Unfortunately, using this type of recommender systems makes the provided courses very similar to Ali's profile. In fact, Ali's profile contains the school's courses, which will make him feel so bored and less motivated to learn more. For this reason, there is a real need to add "Serendipitous Courses" in the Moodle platform to make Ali more motivated and enable him to accumulate further new information. Therefore, the idea is to enhance the recommender system in Moodle by adding the serendipity aspect. In this case, Ali will receive serendipitous courses (3), which will offer him the possibility to improve his skills and capacities with useful, unexpected and novel courses. Thus, based on our solution, Ali would feel very satisfied.

Table 1: Educational Datasets.

Datasets	Repository	Nb of citations	(nb of instances, nb of features)	Purposes
Student Performance Dataset[1] 2014	UCI ML	394	(649,30)	Prediction of students' grade
Educational Process Mining Dataset (EPM)[2] 2015	UCI ML	42	(230318,13)	Predicting learning difficulties, analyzing structured learning behavior or discovering student behavior patterns
Video Game Learning Analytics[3] 2020	Harvard Dataverse		(331,25)	Early Reading and Writing Assessment in Preschool
RecSysTEL Datatel Challenge[4] 2010	Competition	not mentioned	not mentioned	Technology Enhanced Learning
EdNet: A Large-Scale Hierarchical Dataset in Educatio[5] 2020	Competition	not mentioned	780 K users	Collect real students' question-solving logs
Learn Moodle August[6] 2016	Standalone	not mentioned	6119 students	Inspire better teaching practices everywhere

[1] Student Performance Data Set, http://archive.ics.uci.edu/ml/datasets/Student+Performance
[2] Educational Process Mining (EPM): A Learning Analytics Data Set, https://tinyurl.com/y27yduo3
[3] Early Reading and Writing Assessment in Preschool, https://doi.org/10.7910/DVN/V7E9XD
[4] RecSysTEL Datatel Challenge 2010, http://adenu.ia.uned.es/workshops/recsystel2010/datatel.htm
[5] EdNet competition site, http://ednet-leaderboard.s3-website-ap-northeast-1.amazonaws.com/
[6] Learn Moodle August 2016, https://research.moodle.org/158/

3.2 Proposed Architecture to Attend Serendipitous Recommendations

In order to elaborate a serendipity-oriented RS, we build up an architecture that can be summarized in four main layers: Social media, Data extraction, Serendipity dimension extraction and Recommendation. Figure 2 illustrates the proposed architecture.

The second and the third layers aim to erect educational serendipity-oriented data. The Data extraction layer will be detailed in section 4, and the Serendipity dimension extraction layer will be detailed in section 5.

The recommendation layer of our architecture will be addressed in the subsequent work. It aims to build a RS oriented serendipity using the extracted data. The algorithm of recommendation takes place at two stages. The first stage predicts a sequence of k courses (as LR). The second stage applies the re-ranking of k predicted courses according to the dimensions of the serendipity and recommends the course that best verifies the usefulness, unexpectedness and novelty according to the learner's interests and behavior.

4 DATA EXTRACTION

As mentioned earlier in section 2.2, the available educational dataset has several limitations and cannot cover our requirements to achieve serendipity. For this reason, we collected our own dataset corresponding to our needs. Our chief target is to gather data in a legal way via API (Application Program Interface) provided by diverse social media platforms such as YouTube and Linked-In. This choice of source diversity is enacted basically to have data variety with different types of LR such as courses represented by texts, videos, etc.
In our experiment we are confined to extract the data from YouTube using its available API by "beautifulsoupe".

We developed a dataset consisting of three data tables. The first collected data are named "CourseData", where every course is identified with an ID and other features as depicted in table 2. CourseData involves information about 2362 courses represented by 9 features: identifier, title, description, type, course link, number of likes , views and comments as well as the duration.

The second dataset "LearnerDtata" involves in-

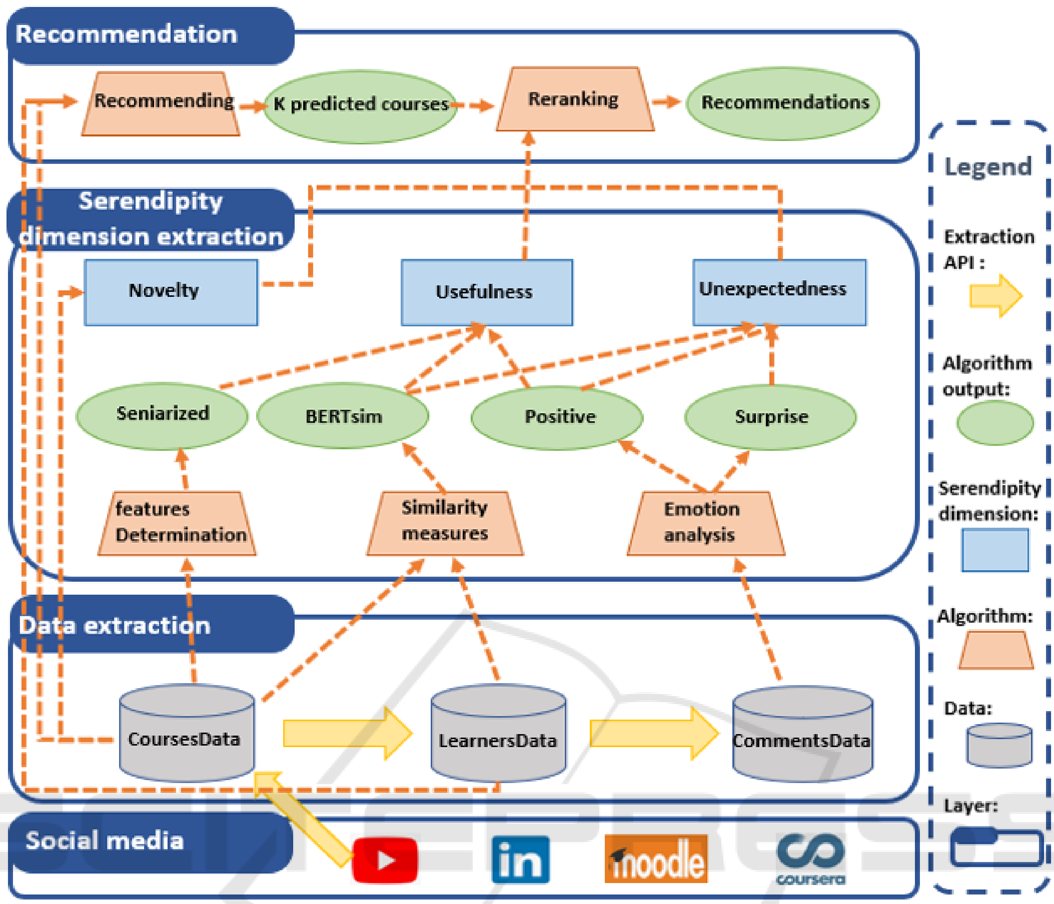

Figure 2: Serendipity-oriented recommendation architecture.

formation about 99394 learners represented by 7 attributes, as plotted in table 3. The learner is identified with his/her name and linked with the information about his/her interactions, some of which characterize his/her behavior.
The extracted data on the learner will be added to his/her profile.

Once the courses data and learner's data are extracted from the Data extraction layer, we switch to the serendipity dimension extraction layer (section3.2).

5 SERENDIPITY DIMENSION EXTRACTION

Notably, the serendipity dimensions that are mostly used in previous works are novelty, unexpectedness and usefulness. However, these dimensions are identified specifically in domains other than online learning. From this perspective, we determined them through emotions analysis algorithms and other algorithms to identify attributes to enrich the extracted data. These dimensions are used in order to provide serendipitous recommendations.

5.1 Usefulness Dimension

Authors in (Kotkov et al., 2016) defined a useful item that a user likes, consumes or is interested in. However, in the educational domain, the usefulness affects equally the quality of the course. As far as our work is concerned, we consider that a useful course should be represented in a pedagogical way and has a positive impact. Additionally, it should be close to the learner's interest. Consequently, we assert that the usefulness of course can be achieved using the equation below.

$$\begin{aligned} \textbf{\textit{Usefulness}} &= (CoursePedagogy = True) \\ &\quad \& \ (CourseMark = Positive) \\ &\quad \& \ (BERTsim > threshold) \end{aligned} \tag{1}$$

Table 2: CourseData.

Features	Description
CourseId	Represents the unique ID of the course
CourseTitle	Represents to the title of the course
CourseDescription	Represents the description of the educational course content
CourseUrl	link of the course.
PublishedDate	Represents the date on which the course is published in the form of time-day-month-year.
ViewsNB	Represents the number of views on the course
LikesNB	Represents the number of learners who likes a course
CommentNB	Represents the number of comments related to the course
CourseDuration	Represents the duration of the course in terms of hours, minutes and seconds.

Table 3: LearnerData.

Features	Description
LearnerName	Name of the learner.
CourseId	Id of course followed by a given learner.
CommentId	Id of the comment done by the user.
CommentURL	Comment link, if does not exist, it will take the value “nan”.
CommentDate	Date time-day-month-years, when the comment is added.
CommentLikes	Number of the likes on the comment.
RepliesCount	Number of replies on the comment.

where the pedagogy of course is verified by this equation:

$$\begin{aligned} CoursePedagogy = (&CourseSeniarization = True) \\ &\& (CourseMark = Positive \\ &|| CourseMark = Neutral) \end{aligned} \tag{2}$$

The learner’s comment describes his/her emotion facing the given course. For this reason, in our analysis we used comments on courses as input. We invested Lexicon-based emotion analysis to classify courses according to their notices if positive, neutral or negative. In fact, we used three lexicon-based approaches (Aljedaani et al., 2022): the TextBlob, VADER and AFINN. Notably, these approaches provide output polarity scores to determine learner’s emotion on a course. Since each model has its own advantages, we chose to use all the three together so as to increase the performance of the labeling. Therefore, we obtained three course’s marks outputs, then we applied a majority algorithm to determine the final course mark (CourseMark), in order to use it as a feature in the data set.

Poor LR structure is one of the main factors for learner dropout. For this reason, we recommend courses organized in a pedagogical way. Thus, we set forward a method to determine whether a course is pedagogical or not. We assumed that a course, in addition to its mark (positive or negative), needs to be well organized and divided into sections by time distribution to be scenarized (CourseSeniarization). In fact, we used the description of course as the input of the algorithm that verifies the scenarization. We have considered that the learner’s interest can be defined by the topic of the taken course. Indeed, the title of the course generally describes its subject matter. In order to verify if the given courses are close to the learner’s interests or not, we implemented a model that verifies the similarity between the course title and the sequence of followed courses in the learner’s profile. We used the high performance semantic similarity BERT (Peinelt et al., 2020), and we supposed that two courses are similar if the result of the model BERTsim>threshold.

5.2 Unexpectedness Dimension

Unexpectedness is the core of the serendipity in the recommendation. As defined in (Kotkov et al., 2016), an unexpected item differs from the profile of the user regardless of whether it is novel or useful. In our case, we define that an unexpected course should have a good mark and make the learner positively surprised. Further more, it should be different from the learner’s profile. Therefore, we applied the equation below:

$$\begin{aligned} \boldsymbol{Unexpectedness} = (&CourseMark = Positive) \\ &\& (CourseSurprise = true) \\ &\& \ course \nexists \ in \ the \ Learner's \ profile \end{aligned} \tag{3}$$

In order to verify if a course can surprise a learner, we analyzed the learner’s emotion by implementing a lexical approach based on an algorithm using a dictionary containing surprising terms. For this analysis, we took the learner’s comments on this course as an input to our algorithms.

5.3 Novelty Dimension

Novelty refers to the ability of recommending new and unprecedented recommendations (Ziarani and Ravanmehr, 2021b). Hence, in order to improve online learning, we need to recommend courses that are novel for the learner. The novelty of the course can be expressed according to this equation:

$$\begin{aligned} \textit{Novelty} = (&\textit{PublishedDate} < \textit{threshold}) \\ &\& \ (\textit{LikesNB} > \textit{avrgLikes}) \end{aligned} \tag{4}$$

A course is considered novel if it is recently published and has a good feedback from a large number of learners. The feedback can be likes, comments or shares.

5.4 Data Enrichment with Dimensions of Serendipity

After applying the previous algorithms based on serendipity, we added new features that are necessary for achieving serendipity dimensions. As a result, we integrated 6 new features to the CourseData, as displayed in table 4:

Table 4: Data enrichment.

Features	Description
CourseLeghth	Refers to the fact whether the length of the course is short, medium or long.
CourseSeniarization	Stands for the fact whether the course is scenarized or not.
CourseType	Refers to the type of course content: text, video, image or audio.
CourseMark	Represents the mark of the learner on the course which can be positive,
CoursePedagogy	Refers to the educational pathway of the course construction, if it is pedagogical or not.

6 EVALUATION

Evaluating a recommender system makes it possible to assess its performance against its objectives. To evaluate a recommender system, two approaches are possible, namely an online (user studies) and an offline evaluation.

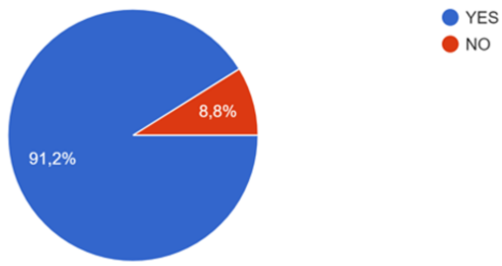

Figure 3: Learner Satisfaction with recommendations.

6.1 Online Evaluation

In the online evaluation, the recommender system is tested by real users investing in a real application. It allows the system not only to generate very reliable results but also to measure the performance of the application in a real-use context. Since the serendipitous recommendations are based on emotional analysis, it is important to conduct a test on real learners to measure user satisfaction through explicit ratings. Users receive the generated recommendations, then rate them.

In our work, we are proposed that we can achieve the relevance of recommendation only when it is characterized by the three dimensions of serendipity (cf. section 5). In order to evaluate our RS (more precisely the dimensions of serendipity), we conducted a real test with 100 learners. Then, we test their satisfaction on serendipity. For this reason, we asked them if they are satisfied with the serendipity of recommendations or not. The result in figure 3 reveals that 91,2% of courses are serendipitous. Therefore, we conclude that the recommendations are relevant.

Afterward, we give a questionnaire from which we test the satisfaction of learners for each dimension. We asked the main questions according to the serendipity dimensions inspired from (Taramigkou et al., 2013). These questions are outlined in table 5.

Table 5: Real learners based evaluation.

Question	Yes	No
Do you think this recommendation is useful for you?		
Have you seen these courses before?		
Are you expecting a suggestion similar to this one?		

As reported in figure 4, most of recommended LR are considered “useful” by (85%), “novel” (70%) and “unexpected” (67%), which implies that the learners tried and appreciated the serendipity of the recommendations.

Table 6: Comparison of obtained results based on serendipity dimensions.

Approach/Serendipity measures	Usefulness	Novelty	Unexpectedness	Precision	Recall	F-measure
(Ziarani and Ravanmehr, 2021a)(Zhang et al., 2021)			X	0.67	0.73	0.69
(Li et al., 2019)	X			0.85	0.93	0.88
(Kaminskas and Bridge, 2016)		X		0.7	0.76	0.72
(Pardos and Jiang, 2020)(Menk et al., 2017)		X	X	0.68	0.75	0.71
Our Approach	X	X	X	**0.91**	**1**	**0.95**

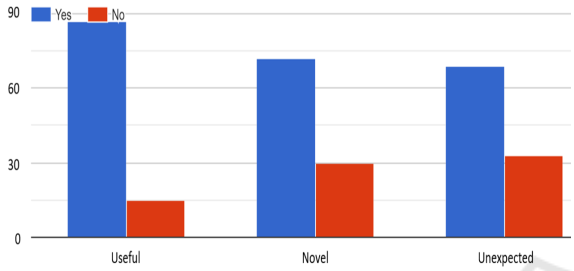

Figure 4: Serendipity dimension satisfaction.

6.2 Offline Evaluation

In order to make the evaluation of the recommender system more accurate, the offline evaluation is based on a well-defined mathematical calculation, in which the values of the precision, recall, and F-measure are used.

The precision (Pre) determines the probability that a recommended item is relevant, by dividing the Number of Relevant Recommendations (NRR) by the Total Number of Recommendations(TNR)

$$\boldsymbol{Pre} = NRR/TNR \tag{5}$$

The recall (Rec) highlights the Number of Relevant Recommendations that were returned to the user out of the Total Number of Relevant Recommendations.

$$\boldsymbol{Rec} = NRR/TNRR \tag{6}$$

The F-measure (F-me) considers both the last two measures simultaneously and indicates the overall relevance of the list of recommendations.

$$\boldsymbol{F\text{-}me} = (2 * Pre * Rec)/(Pre + Rec) \tag{7}$$

In order to study the performance and reliability of the proposed approach, we have taken into account the different dimensions of serendipity. We compared our approach with the following state-of-art approaches in table 6.

From the results of the table, we can observe that relying only on one or two dimensions of serendipity is somewhat less satisfying with F-measure values between 0.69 and 0.88. We conclude that using all three dimensions together gives better results with an F-measure value of 0.95.

7 CONCLUSION

In this paper, we are basically interested in achieving serendipitous recommendations of LR. For this reason, we investigated RS as well as serendipity dimensions and challenges. We notice that the most crucial challenges in this context are the availability of educational datasets and the determination of serendipity dimensions. First, in order to explain our goal and method, we presented a motivational scenario and the architecture of the proposed approach. The latter consists of four layers: social media, Data extraction, Serendipity dimension extraction, and Recommendation. In the data extraction layer, we defined a dataset describing the learner and the characteristics of the taken courses from social media. Then, we applied some algorithms to determine the three serendipity dimensions: Usefulness, Novelty, and Unexpectedness. Indeed, these dimensions allow us to provide ”serendipitous” recommendations.

We undertook an online and offline evaluation for learners who proved the relevance of serendipitous recommendations.

In future research work, we will detail the fourth layer. We aspire to adapt and test the recommendation layer of the proposed approach in such Learning Management Systems as Moodle.

ACKNOWLEDGEMENTS

This work was financially supported by the PHC Utique program of the French Ministry of Foreign Affairs and Ministry of higher education and research and the Tunisian Ministry of higher education and scientific research in the CMCU project number 22G1403.

REFERENCES

Aljedaani, W., Rustam, F., Mkaouer, M. W., Ghallab, A., Rupapara, V., Washington, P. B., Lee, E., and Ashraf, I. (2022). Sentiment analysis on twitter data integrating textblob and deep learning models: the case of us airline industry. *Knowledge-Based Systems*, 255:109780.

Dien, T. T., Thanh-Hai, N., and Thai-Nghe, N. (2022). An approach for learning resource recommendation using deep matrix factorization. *Journal of Information and Telecommunication*, 6(4):1–18.

Fraihat, S. and Shambour, Q. (2015). A framework of semantic recommender system for e-learning. *Journal of Software*, 10(3):317–330.

Guo, J., Ji, W., Yuan, J., and Wang, X. (2022). Multi-channel orthogonal decomposition attention network for sequential recommendation. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 288–300. Springer.

Guo, T., Wen, Y., Wang, F., and Hou, J. (2019). Learning resource recommendation based on generalized matrix factorization and long short-term memory model. In *2019 IEEE International Conference on Cloud Computing Technology and Science (CloudCom)*, pages 217–222. IEEE.

Hermawan, D. (2021). The rise of e-learning in covid-19 pandemic in private university: challenges and opportunities. *IJORER: International Journal of Recent Educational Research*, 2(1):86–95.

Kaminskas, M. and Bridge, D. (2016). Diversity, serendipity, novelty, and coverage: a survey and empirical analysis of beyond-accuracy objectives in recommender systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 7(1):1–42.

Kotkov, D., Veijalainen, J., and Wang, S. (2020). How does serendipity affect diversity in recommender systems? a serendipity-oriented greedy algorithm. *Computing*, 102(2):393–411.

Kotkov, D., Wang, S., and Veijalainen, J. (2016). A survey of serendipity in recommender systems. *Knowledge-Based Systems*, 111:180–192.

Kundu, S. S., Sarkar, D., Jana, P., and Kole, D. K. (2021). Personalization in education using recommendation system: An overview. *Computational Intelligence in Digital Pedagogy*, pages 85–111.

Li, X., Jiang, W., Chen, W., Wu, J., and Wang, G. (2019). Haes: A new hybrid approach for movie recommendation with elastic serendipity. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, pages 1503–1512.

Menk, A., Sebastia, L., and Ferreira, R. (2017). Curumim: A serendipitous recommender system for tourism based on human curiosity. In *2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 788–795. IEEE.

Mihaescu, M. C. and Popescu, P. S. (2021). Review on publicly available datasets for educational data mining. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 11(3):e1403.

Nguyen, T. T., Hui, P.-M., Harper, F. M., Terveen, L., and Konstan, J. A. (2014). Exploring the filter bubble: the effect of using recommender systems on content diversity. In *Proceedings of the 23rd international conference on World wide web*, pages 677–686.

Pardos, Z. A. and Jiang, W. (2020). Designing for serendipity in a university course recommendation system. In *Proceedings of the tenth international conference on learning analytics & knowledge*, pages 350–359.

Peinelt, N., Nguyen, D., and Liakata, M. (2020). tbert: Topic models and bert joining forces for semantic similarity detection. In *Proceedings of the 58th annual meeting of the association for computational linguistics*, pages 7047–7055.

Taramigkou, M., Bothos, E., Christidis, K., Apostolou, D., and Mentzas, G. (2013). Escape the bubble: Guided exploration of music preferences for serendipity and novelty. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 335–338.

Troudi, A., Ghorbel, L., Amel Zayani, C., Jamoussi, S., and Amous, I. (2021). Mder: Multi-dimensional event recommendation in social media context. *The Computer Journal*, 64(3):369–382.

Vora, M., Barvaliya, H., Balar, P., and Jagtap, N. (2020). E-learning systems and moocs-a review. *Int. J. Res. Appl. Sci. Eng. Technol*, 8(9):636–641.

Zhang, M., Yang, Y., Abbas, R., Deng, K., Li, J., and Zhang, B. (2021). Snpr: A serendipity-oriented next poi recommendation model. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 2568–2577.

Zhang, Q., Wang, S., Lu, W., Feng, C., Peng, X., and Wang, Q. (2022). Rethinking adjacent dependency in session-based recommendations. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 301–313. Springer.

Ziarani, R. J. and Ravanmehr, R. (2021a). Deep neural network approach for a serendipity-oriented recommendation system. *Expert Systems with Applications*, 185:115660.

Ziarani, R. J. and Ravanmehr, R. (2021b). Serendipity in recommender systems: a systematic literature review. *Journal of Computer Science and Technology*, 36(2):375–396.