Teacher Educational Resources Recommendation in the COVID-19 Context

Nader N. Nashed[1,2] [a], Christine Lahoud[2] [b] and Marie-Hélène Abel[1] [c]

[1]HEUDIASYC, Université de Technologie de Compiègne, Compiègne, France

[2]Université Française d'Égypte, Cairo, Egypt

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Abstract: The educational process is greatly impacted by the coronavirus pandemic (COVID-19) and this impact outreaches teachers, learners, and all participants. This pandemic is responsible for multiple modifications to the traditional teaching and learning techniques and technologies which leads to social and cultural changes. Due to the accompanied social changes, teachers are experiencing different degrees of stress, burnout, and work difficulties during learning new technologies and preparing to their courses' contents. Teacher's sentimental state can be represented by one's mood and can present an accurate measurement to a teacher experiencing the mentioned difficulties. Accordingly, this study proposes a possible solution for one of the main participants in the educational process, the teacher, by recommending him educational resources to cope with stress and prevent burnout. The proposed recommender system analyses the teacher's mood and accordingly recommends educational resources that can enhance the teacher's sentimental state. Through the investigation of this proposal, we found that the enforcement of the sentimental state impacts the resulting recommendations that are presented to teachers.

1 INTRODUCTION

During the current ever-changing circumstances, the educational process, along with everything, is experiencing significant adjustments and adaptations in favor of learners to cope with this coronavirus pandemic (COVID-19) span. The most significant adjustment to the educational system is the rapid shifting towards online teaching and learning environments (Peimani and Kamalipour, 2021). The online teaching/learning environments form a major challenge for the educational process, as a result, participants lose control over the participation hours which greatly affects their psychological and sentimental states (Akour et al., 2020). Therefore, teachers, like many professions, are forced to have an unstable work-life balance due to shifting towards teleworking (Thulin et al., 2019). Stress and burnout are closely associated with the intensive usage of new technologies by teachers as a cause of lack of previous adaptation to these technologies (Riedl et al., 2012).

Prior to the coronavirus pandemic, teachers experience multiple struggles including stress and work overload (Nashed et al., 2022). During the pandemic, these struggles have been highlighted and intensified by the lack of training and the inequality of access to modern technology in the different regions (Jain et al., 2021; Scherer et al., 2021). (Friedman, 2000) highlighted three components of burnout: sentimental exhaustion, detachment from the job, and a lack of personal accomplishment. With the proper training, teachers can overcome these causes and prevent the psychological risk accompanied with health crisis (Jenaro et al., 2007). This training develops the professional capabilities of teachers and accordingly, increases their self-esteem and eliminates the feel of guilt (Jenaro et al., 2007). Training is considered as a type of educational resources along with academic improvement activities, skills in a specific subject, innovative teaching methodologies, stress management at work, time management, or even one or more peers for work collaboration and experience sharing. Moreover, the multiple contexts in which any teacher coexists must be considered to provide the teacher with proper training (Cooper and Olson, 2020).

As a result, this pandemic enforces the considera-

[a] https://orcid.org/0000-0001-5849-1322
[b] https://orcid.org/0000-0002-4520-634X
[c] https://orcid.org/0000-0003-1812-6763

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tion of one's sentimental context as one of the indications to the stress and burnout (Herman et al., 2018; Skaalvik and Skaalvik, 2020). During previous research, the teacher's multiple contexts were identified, and their impact was discussed (Flores and Day, 2006). These contexts comprise the living environment context as well as the working environment context to shape the major contextual factors that affect the teacher's performance. Mood, emotional commitment, and flow shape the sentimental context of the teacher (Bishay, 1996).

In this paper, we explain the usage of merging of the sentimental context, raised by COVID-19, into the already existing multiple contexts of teachers to provide personalized educational resources recommendations. Section 2 provides a background review of related work to this one. Then, Section 3 contains an illustration of the proposed methodology. Moreover, Section 4 discusses the usage of this proposition with the aid of examples. Finally, Section 5 concludes this paper and introduces future perspectives.

2 RELATED WORK

The physical and mental health of teachers are strongly related to their working efficacy (McIntyre et al., 2017; Lachowska et al., 2018; Oberle et al., 2020). The resultant mood swings, during the current times, are responsible for teacher efficacy and performance (Frenzel, 2014). In addition, it is directly related to the teacher's burnout which directly affects the learners (Mérida-López and Extremera, 2017; Heutte et al., 2016). Educational/training resources can act as a mitigator to COVID-19 effects on teachers such as burnout and stress (Lizana et al., 2021). These educational resources are categorized into internal resources, such as classroom management and instructional resources, and external resources, such as supporting educational resources. This approach is said to be efficient if teachers are provided with personalized strategies and resources to acquire new skills and facilitate the classroom management (Lizana et al., 2021).

During the current COVID-19 era, digital technologies are essential support for teaching and learning processes in various fields and different educational levels (Perifanou et al., 2021; Mukhtar et al., 2020). Educational resources recommender systems (ERRS) aid this purpose by providing personalized educational resources recommendations for each teacher. Traditionally, ERRS targets learners by recommending learning objects or materials in addition to performance evaluation (Zhang et al., 2021). The importance of the context-aware recommenders arises recently to consider the social and environmental conditions (Nilashi et al., 2020). (De Meo et al., 2017) introduced a social networking context-aware recommender system approach by combining trust relationships and skills evaluation to reform the online classrooms. On the other hand, (Klašnja-Milićević et al., 2018) combines social tagging and sequential patterns to provide context-aware recommendations in an e-learning environment. (Moore et al., 2019) monitors student's progress in order to provide personalized performance evaluation without using face-to-face tutorial sessions and then recommends learning materials. As for the teacher centered ERRS, (Cobos et al., 2013) introduced a recommender approach to teachers by detecting the pedagogical patterns from the online recorded information based on the class context. The systematic reviews conducted by (Zhang et al., 2021) and (Imran et al., 2021) prove that research efforts are directed towards learners' context with nearly neglection to teacher context which was the motivation of this research.

3 PROPOSED APPROACH

The task of providing personalized recommendations is a complicate process, moreover, the consideration of teacher's/user's context increases the difficulty level of this task. At the beginning, teacher's multiple contexts are summarized into living environment, working environment and sentimental state within the organizational management system, MEMORAe, and are represented by teacher-context ontology (TCO), mood detection ontology (MDO), as well as MEMORAe ontology (MCC) (Nashed et al., 2021). Each context is defined by a teacher-dependent set of factors and dimensions which needs to be precisely selected in order to avoid the unification of these factors. However, the selection of these factors cannot grantee accurate representation of teacher's contexts, instead, the factors' weighting is another important step towards the precise teacher's contexts representation. Therefore, the proposed approach, as shown in Fig. 1, introduces a first step of mood detection using MoodFlow@doubleYou (Andres et al., 2021) and user activity tracking using the MEMORAe SoIS for a teacher. Afterwards, the contextual factors are extracted and weighted with a mood-enforcing approach with respect to the teacher. These contextual factors are then used to find matching teachers with similar context to the current teacher which are stored into a

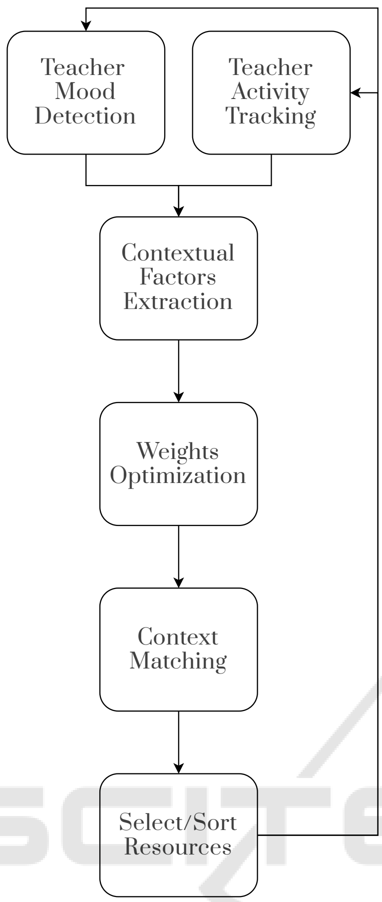

Figure 1: Overview of the approach architecture.

sorted list according to a set of SWRL rules[1]. At the end, a list of educational resources recommendations is retrieved for this teacher using the list of matching teachers. Accordingly, this paper proposes a methodology to select and weight the contextual factors to facilitate the educational resources recommendation for teacher.

3.1 Ontology Representation

The ontology representation of the aforementioned contexts, as shown in Fig. 2, facilitates the interconnectivity between them, in addition to the data representation advantage. TCO represents a teacher as a person that is related to two types of environments: living and working environments. Object properties are used to associate descriptive objects to each environment such as location, area type, population, etc. The educational institution, in which the teacher works, is related to the work environment to facilitate the working conditions representation.

[1]https://www.w3.org/Submission/SWRL/

While MDO ontology represents the mood of a certain teacher using the three-level representation of mood: negative, neutral, and positive moods. The teacher's mood is captured while interacting with educational resources using MoodFlow@doubleYou technology. The sentimental context is represented through the associated mood concept with each tracked activity that is recorded for each user account concept of MEMORAe's person.

MCC ontology is an organization-management ontology that describes the data model of MEMORAe SoIS (Abel et al., 2007). This SoIS is used to manage sub-ontologies and in our case, teachers are introduced to an organizational representation of one of their educational courses in the form of notions/concepts. An example, is shown in Fig. 3, illustrates the ontology representation of ”PRE103” course which is an introductory course to programming languages and algorithms. Sections and subsections of ”PRE103” content are represented by nodes in a semantic mapping manner where each node acts as a sharing space regarding a certain topic. This course is divided into sub-node collections of tutorials (TD) and practical exercises (TP) which allows the teacher to attach educational resources related to each of the TD and TP nodes. Teacher's interactions with node-attached resources, are tracked by the system and are associated with one of the mood levels of MDO.

This mechanism empowers the data representation and retrieval of the teacher's context and assists the following step of contextual factors selection and weighting.

3.2 Contextual Factors Extraction and Teacher Matching

A multi-step approach, as shown in Fig. 1 and Algorithm 1, is proposed to extract contextual factors, optimize their weights, find matching teachers' contexts, and recommend educational resources according to the matching teachers list. Table 1 includes the mentioned abbreviations in this sub-section to help the reader to follow the multiple algorithms and the sub-algorithms. At the beginning, Algorithm 1 selects a set of contextual factors for a teacher's context C^T, as shown in Algorithm 3, and computes the final weights for each of these factors, as shown in Algorithm 2. Then, a new teacher's context C_0^T is defined with the utilization of the selected factors. Accordingly, the algorithm retrieves a list of matching teachers according to the newly defined context, as shown in Algorithm 4. Afterwards, the obtained list is

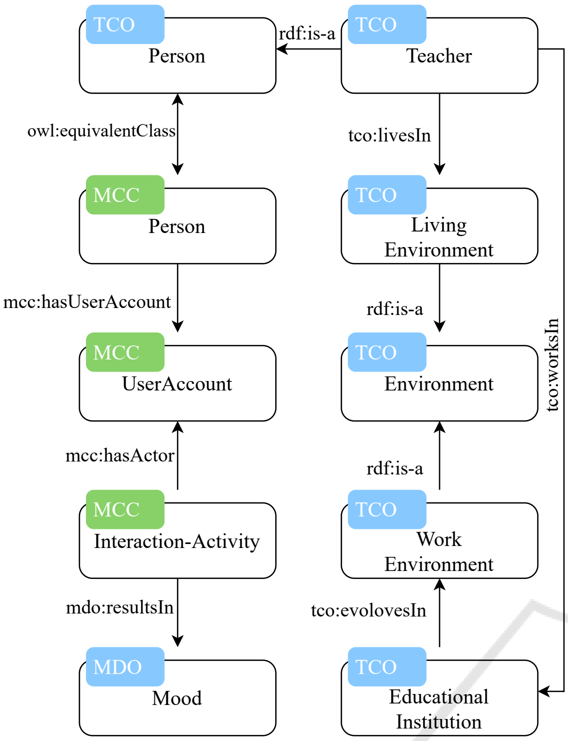

Figure 2: Partial Tbox of ontology representation of teacher's multiple contexts.

scored and sorted according to a set of SWRL rules, as shown in Algorithm 5. At the end, the obtained matching teachers list is used to recommend educational resources for the current teacher T.

Algorithm 2 illustrates the process of computing the initial weights W_{init} of a teacher context C^T by using the variance-based extraction of contextual factors for teacher T according to the collected interactions' history H^T with a set of nodes in which each node is connected to a set of resources R, as shown in Algorithm 3. The initial weights W_{init} are optimized using an optimization algorithm such as particle swarm optimization (PSO) (Marini and Walczak, 2015) with the root mean squared error (RMSE) (Equation 1) as the fitness function FF which evaluates the final weights W_{final} of each selected contextual factor.

$$RMSE(rating^{predict}_{resr}, rating^{actual}_{resr}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(rating^{predict}_{resr_i} - rating^{actual}_{resr_i})^2} \quad (1)$$

where:

- n: number of predicted ratings
- $rating^{predict}_{resr_i}$: predicted rating for a resource $resr_i$
- $rating^{actual}_{resr_i}$: actual rating for a resource $resr_i$

Table 1: Abbreviations List.

Abbrev.	Definition
TCO	Teacher-Context Ontology
MDO	Mood Detection Ontology
MCC	MEMORAe Ontology
T	a teacher
T_s	selected teacher
$resr$	an educational resource
$rating$	a rating provided by teacher T for a resource $resr$
F	set of contextual factors corresponding to a teacher T
f	a contextual factor
C^T_{work}	working environment context of teacher T
C^T_{living}	living environment context of teacher T
$C^T_{sentimental}$	sentimental context of teacher T
C^T_0	selected context of teacher T
C^T_{all}	list of selected contexts of all teachers
H^T	history of teacher T
w	the weight of a contextual factor f
W_{init}	initial weights of contextual factors F for a teacher T
W_{final}	final weights of contextual factors F for a teacher T
FF	fitness function
$coef_{mood}$	mood contextual factor enforcing coefficient
thr_1	similarity threshold
thr_2	weight threshold
thr_{sim}	semantic similarity threshold
thr_{score}	SWRL rules score threshold
nb_T	number of similar teachers for a certain teacher T
Sim_{total}	total similarity score
sim^{resr}	similarity score for a single resource $resr$
sim^{resr}_{var}	similarity variance for a single resource $resr$
R_{SWRL}	set of SWRL rules
IC	Information Content
LCS	Least Common Subsumer

Algorithm 3 shows the process of selecting the contextual factors from the multiple contexts of a teacher: C^T_{work}, C^T_{living}, and $C^T_{sentimental}$. The same steps are performed in accordance with a resource $resr$ foreach context of teacher T. First, we calculate the similarity score for each teacher who interacts with the same resource $resr$ and then, we eliminate teachers with scores less than the similarity threshold thr_1. In order to highlight the sentimental context during this pandemic era, a coefficient multiplier

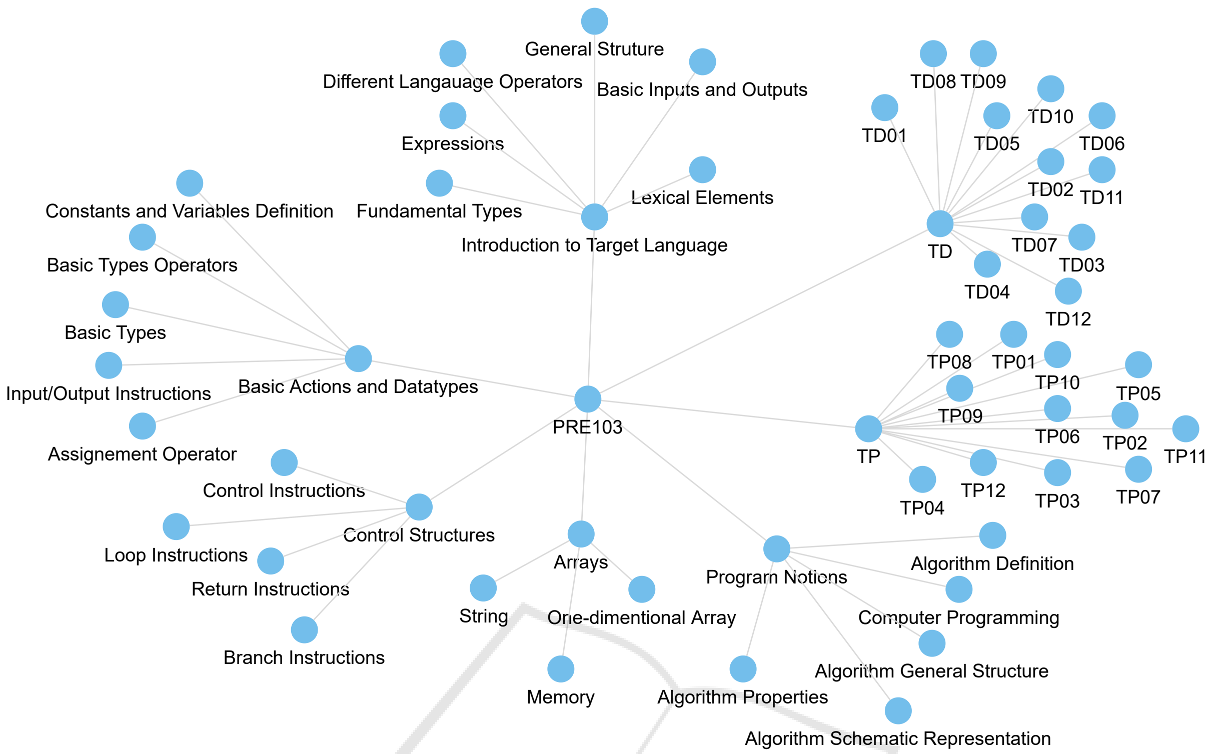

Figure 3: Partial screenshot of ”Introduction to programming course (PRE103)” within the MEMORAe system’s user interface.

Algorithm 1: An overview of the proposed algorithm.

Input: C^T_{work} : current working environment context of a teacher T
C^T_{living} : current living environment context of a teacher T
$C^T_{sentimental}$: current sentimental context of a teacher T
H^T : history of current teacher T
Output: $sortedList$: sorted list of all matching teachers
begin
W_{final} = contextsFactorsExtraction(C^T_{work}, C^T_{living}, $C^T_{sentimental}$, H^T);
C^T_0 = getTeacherContext(W_{final});
$MatchingTeacherList$ = teachersContextMatching(C^T_0, W_{final});
$sortedTeacherList$ = SWRLsortList($MatchingTeacherList$);
$resourcesList$ = getRecommendations(H^T,$sortedTeacherList$);
return sortedList;
end

is used with the mood contextual factor to enforce the teacher-teacher context similarity which results in higher probability of mood factor selection within the final set of factors. Afterwards, we compute the mean value between the average similarity across similar teachers interacting with the resource *resr* and the variance value within this list to calculate the initial weight w_{init} for this resource *resr*. If w_{init} is less than the weight threshold thr_2, the corresponding factor will be eliminated from the final set of selected contextual factors which is used to construct the final list of matching teachers.

Through Algorithm 4, this context matching step is responsible for finding the list of teachers with the same set of selected contextual factors C^T_j matching the current teacher’s set of contextual factors C^T_0 by calculating the Jiang-Conrath semantic similarity between both contextual factors (Jiang and Conrath, 1997). The Jiang-Conrath similarity takes into account the information content (IC) for

Algorithm 2: Teacher's contextual factors weighting algorithm.

Input: C^T_{work} : current working environment context of a teacher T
C^T_{living} : current living environment context of a teacher T
$C^T_{sentimental}$: current sentimental context of a teacher T
H^T : history of current teacher T
FF : fitness function
Output: W_{final}=$\{< f_1, w_1 >, \ldots, < f_n, w_{n'} >\}$: set of final weights w_i for each of the selected n' context factor f_i from the n initial context factors where $n' < n$.
begin
W_{init}=selectFactors(C^T_{work}, C^T_{living}, $C^T_{sentimental}$, H^T);
W_{final}=optimizeWeights (W_{init},FF);
return W_{final}
end

each selected factor (semantic concept) in the set of contextual factors for C^T_0 and C^T_j as in Eq. 2. This similarity measure is not fulfilled until the distance $distance$ between any two selected factors (semantic concepts) f_{k_0} and f_k is obtained using the least common subsumer (LCS) as in Eq. 3. The semantic similarity threshold thr_{sim} is responsible for omitting the least similar teachers from the final list. This teachers list is passed to be evaluated using the SWRL rules.

$$Sim(f_{k_0}, f_k) = \frac{1}{D(f_{k_0}, f_k)} \quad (2)$$

$$D(f_{k_0}, f_k) = IC(f_{k_0}) + IC(f_k) – (2 * IC(LCS(f_{k_0}, f_k)) \quad (3)$$

Afterwards, the list of teachers are sorted using SWRL semantic reasoning rules in Table 2 to ensure the correctness of each list element as shown in Algorithm 5. A teacher in the list obtains a scoring unit if a SWRL rule is satisfied. At the end, the total score of a teacher is compared against the SWRL rules score threshold thr_{swrl}. If the teacher does not pass this condition, the list item will be eliminated. The final sorted list is returned to be used for providing resource recommendations.

Collaborative filtering recommendation approach is followed to provide educational resources' recommendations for the teacher T using the two similarity measures that are calculated during the previous algorithm steps: semantic similarity score and SWRL rules similarity. Finally, the teacher is asked to interact with these recommendations within MEMORAe system, meanwhile, the activities and the sentimental state are monitored.

4 DISCUSSION

In this approach, we enforce the sentimental state of teachers during the COVID-19 pandemic context by enhancing the process of finding proper educational resources recommendations as introduced in Subsection 3.2. This enhancements are noticeable in two main phases of the proposed approach: contextual factors extraction in Algorithm 3 and the sorting of the matching teachers list using SWRL rules in Algorithm 5. The output results can be greatly affected according to these new enhancements which is discussed during this section.

4.1 Contextual Factors Selection

For better evaluation of this enhancement's impact on the factors selection, we discuss it using an actual example to compare resulting output with and without the sentimental state condition in Algorithm 3, line 13.

Scenario 1: Let's assume that Teacher 1 T_1 has the following contextual factors for each context:
C^T = {Age, Education, Language, TeacherLevel, FieldofScience, ...}
C^T_{work} = {AreaType, Country, Population, ...}
C^T_{living} = {AreaType, Country, Population, ...}
$C^T_{sentimental}$ = {MoodLevel, CurrentMood, AverageMood, ...}

When the algorithm is executed without the mentioned condition, it generates a vector of selected and weighed contextual factors as follows:
W = {<Language,0.12>, <FieldofScience,0.35>, <MoodLevel,0.16>, <WorkingPlace,0.33>, <LivingLocation,0.14>}

Algorithm 3: Variance-based teacher contextual factors selection algorithm.

Input: $(C^T_{resr})_{work}$=(T,F,$rating$,$resr$) : current working context of a teacher T and concerning the current resource *resr* with rating r, represented by context factors F.
$(C^T_{resr})_{living}$=(T,F,$rating$,$resr$) : current living context of a teacher T and concerning the current resource *resr* with rating r, represented by context factors F.
$(C^T_{resr})_{sentimental}$=($T$,$F$,$rating$,$resr$) : current sentimental context of a teacher T and concerning the current resource *resr* with rating r, represented by context factors F.
H^T : history of current teacher T.
thr_1 : given similarity threshold.
thr_2 : given weight threshold.
$coef_{mood}$: mood contextual factor enforcing coefficient.
Output: W_{init}=$\{< f_1, w1_{init} >, \ldots, < f_{n'}, w_{n'_{init}} >\}$: set of initial weights $w_{i_{init}}$ for each of the n' context factor f_i.
begin
$W_{init} = \{\phi\}$;
for all $C^T_{resr} \in ((C^T_{resr})_{work}, (C^T_{resr})_{living}, (C^T_{resr})_{sentimental})$ **do**
  for all $f_k \in F$ **do**
    $nb_T = 0$;
    $Sim_{total} = 0$;
    for all $< resr_j, c_j^{T_s} > \in H^T$ **do**
      if $(resr_j == resr)$ **then**
        similar(T_s,T) = calculateSimilarity(C^T_{resr},C^{T_s});
        if (similar(T_s,T) $\geq thr_1$) **then**
          nb_T++;
          $rating_{T_s}$ = getRating(T_s,$resr$);
          $similarTeachersList$.add($rating_{T_s}$);
          if ($f_k ==$ '*mood*' && (getMood(T_s) $==$ '*positive*' $||$ getMood(T_s) $==$ '*neutral*')) **then**
            similar(T_s,T) *= $coef_{mood}$;
          end if
          Sim_{total} += similar(T_s,T);
        end if
      end if
    end for
    $sim^{resr} = \frac{Sim_{total}}{nb_T}$;
    sim^{resr}_{var} = getVariance($similarTeachersList$);
    $w_{k_{init}}$ = average(sim^{resr}, sim^{resr}_{var});
    if $(w_{k_{init}} \geq thr_2)$ **then**
      W_{init} = addFactor($< f_k, w_{k_{init}} >$);
    end if
  end for
end for
return W_{init};
end

The resulting contextual factors' list shows that the *MoodLevel* factor obtains low weight with respect to other factors which accordingly affects the final list of recommendations.

However, when we re-run the same algorithm with the mentioned condition, we obtain the following vector:
W = {<Language,0.1>, <FieldofScience,0.35>, <MoodLevel,0.4>, <WorkingPlace,0.28>, <LivingLocation,0.05>}

Therefore, the difference between the weights in both cases, illustrates the noticeable effect of the enforcing coefficient on the resulting vector of contextual factors.

4.2 SWRL Rules Utilization

Through this subsection, we illustrate the effect of enforcing various measures using semantic SWRL rules for a better context representation in this pandemic period. The experience level (Rule 1), sentimental

Algorithm 4: Teacher context matching algorithm.

Input: (C_0^T) : selected contextual factors of current teacher T_0.
$W=\{<f_1, w_1>, \ldots, <f_n, w_n>\}$: set of final weights w_i for each of context factor f_i.
thr_{sim} : given similarity threshold.
Output: $MatchingTeacherList_{T_0}=\{<T_1, Sim_1>, \ldots, <T_m, Sim_m>\}$: list of all matching teachers to current teacher T_0
begin
MatchingTeacherList= $\{\phi\}$;
for all $C_j^T \in C_{all}^T$ **do**
  $Sim_j^T = 0$;
  for all $f_k \in C_j^T$ **do**
    distance = IC(f_{k_0}) + IC(f_k) – (2 * IC(LCS(f_{k_0},f_k)));
    sim(f_{k_0},f_k) = $\frac{1}{distance}$;
    Sim_{T_j} += sim(f_{k_0},f_k) * w_k;
  end for
  if $Sim_{T_j} >= thr_sim$ **then**
    MatchingTeacherList.add($<T_j, Sim_{T_j}>$);
  end if
end for
MatchingTeacherList.sort();
return MatchingTeacherList;
end

Algorithm 5: SWRL rules scoring algorithm.

Input: T_0 : current teacher
$MatchingTeacherList$: list of all matching teachers to current teacher T_0
$R_{SWRL}=\{r_1, \ldots, r_8\}$: set of SWRL rules
thr_{swrl} : given SWRL rules score threshold
Output: $sortedList$: sorted list of matching teachers to current teacher T_0 with respect to the obtained SWRL rules score
begin
MatchingTeacherList= $\{\phi\}$;
for all $T_i \in MatchingTeacherList$ **do**
  $score_{T_i} = 0$;
  for all $r_j \in R_{SWRL}$ **do**
    $result$ = applySWRL(r_j,T_i,T_0);
    if $T_i \in result$ **then**
      $score_{T_i}$++;
    end if
  end for
  if $score_{T_i} \geq thr_{swrl}$ **then**
    $MatchingTeacherList[T_i, score] = score_{T_i}$;
  else
    $MatchingTeacherList$.delete(T_i);
  end if
end for
$sortedList = MatchingTeacherList$.sortByScore();
return $sortedList$;
end

context of a teacher (Rule 2), working context (Rule 6,7), living context (Rule 4,5), and field of experience (field of science) (Rule 8), spoken languages (Rule 3) are the enforced factors in the SWRL rules scoring. The SWRL rules is utilized to enhance the matching similarity scores for the mentioned factors. Scenario 2 illustrates the impact of SWRL rules in enforcing the desired factors.

Scenario 2: Assuming that teacher T_1 has a negative mood while interacting with an educational resource, it is found that teachers T_2 and T_3 are possible matches for this teacher as shown in Fig. 4. The extraction and weighting algorithm produces a list of matching teachers: T_2 and T_3 with 0.76 and 0.62 respective scores. Therefore, the algorithm uses the similarity between T_1 and T_2 to generate the list of resources' recommendation. The enforcement of positive mood as a contextual factor, using the SWRL rules, increases the similarity score of T_2 by 0.34 which means this teacher would not be included into the list of matching teachers.

W = {<Lang,0.1>, <FieldofScience,0.35>, <MoodLevel,0.4>, <WorkingPlace,0.28>, <LivingLocation,0.05>}

T_1 = {{Lang1,Lang2}, FieldofScience1, NegativeMood, SmallCity, SmallCity}
T_2 = {{ Lang1, Lang2, Lang3}, FieldofScience1, PositiveMood, LargeCity, SmallCity}
T_3 = {{Lang2,Lang3}, FieldofScience1, Negative-

Mood, SmallCity, SmallCity}

$Sim(1,2) = (1*0.1+1*0.35+1*0.4+0*0.28+1*0.05)/1.18 = 0.76$
$Sim(1,3) = (0.5*0.1+1*0.35+0*0.4+1*0.28+1*0.05)/1.18 = 0.62$

Accordingly, we can say that introducing these SWRL rules provides resources that generate positive mood with other teachers. These SWRL rules can be replaced with other roles or modified to follow different approaches. For instance, if we replace Rule 8 with another rule that ensures the exact match between the teachers' field of science, the order of the matching teachers' list will be executed differently and therefore, the output recommendations will be impacted. Moreover, we can increase the number of rules to achieve more adjustment to the matching list and accordingly, the final provided recommendations, which provides us with a flexible algorithm that can achieve different levels of adaptation according to our research motivation.

5 CONCLUSION

This paper endorses the usage of context-aware approach to recommend educational resources to teachers during this COVID-19 era. Also, it introduces the sentimental state enforcement during the context matching phase which provides the teacher with positive-mood recommendations. The proposed approach introduces new methodology for selecting and sorting recommendations to generate the final list using SWRL semantic reasoning rules. This work is considered as a first step to explore the context-aware recommender approach and highlight the sentimental state importance during these difficult times. Further assessments are needed to validate this proposal along with real-time experiments.

This work is considered as a first step to explore the context-aware recommender approach and highlight the sentimental state importance during these difficult times. Further assessments are needed to validate this proposal along with real-time experiments. In addition, it can be strengthened through exploring different approaches. Using this approach, a dataset can be created to facilitate the research in the teacher's sentimental state and its relation to the other contexts in which the teacher coexists. This suggestion can lead to a possible computational overhead avoidance. Other approaches can be investigated with the factor's weight optimization using deep learning techniques.

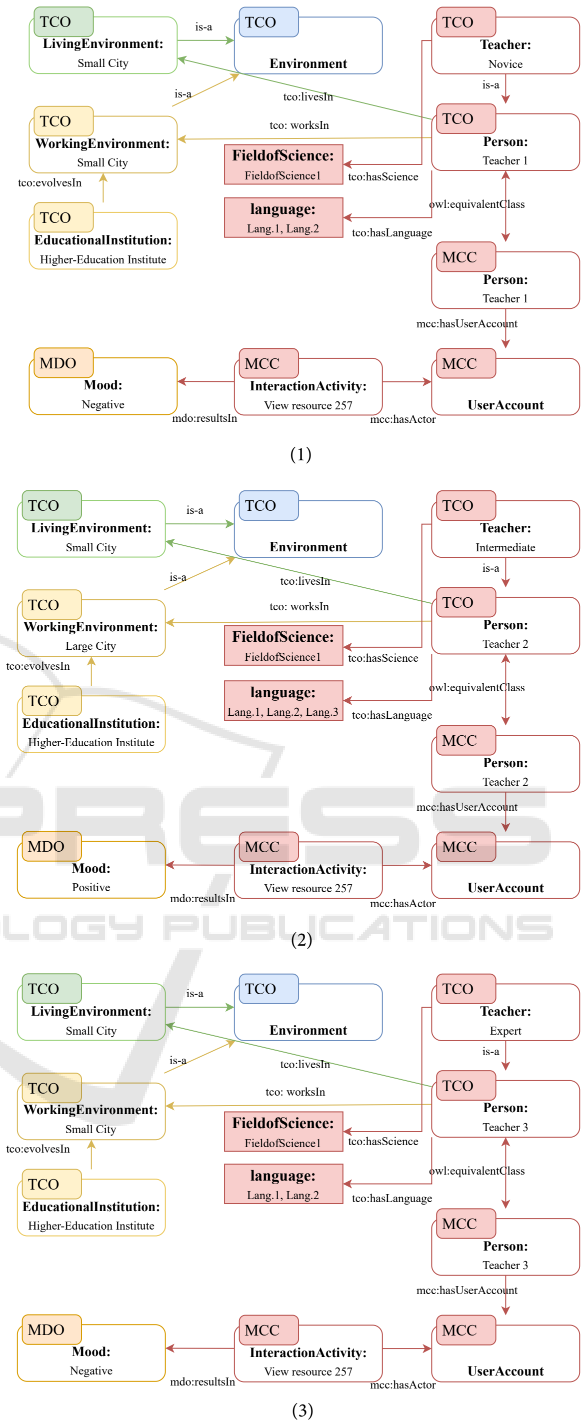

Figure 4: Partial Abox instance of the ontology representation of teachers 1, 2, and 3.

Table 2: SWRL rules for peer's list sorting.

#	SWRL Rule
1	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^tco:teacher(?ts)^tco: hasYearsOfExperience(?ts,?exs)^swrlb:greaterthan(?exs,?ex) $\Longrightarrow$ sqwrl:select(?ts)
2	mcc:InteractionActivity(?e)^mcc:hasActor(?e,?acc)^mdo:resultsIn(?e,?m)^mdo:mood(?m) ^mdo:hasValue(?m,?v)^mcc:hasActor(?e,?accs)^mdo:resultsIn(?e,?ms)^mdo:mood(?ms)^mdo: hasValue(?ms,?vs)^swrlb:greaterthan(?vs,?v) $\Longrightarrow$ sqwrl:select(?ts)
3	tco:teacher(?t)^tco:hasLanguage(?t,?lan)^tco:teacher(?ts)^tco:hasLanguage(?ts,?lans)^swrlb: contains(?lan,lans) $\Longrightarrow$ sqwrl:select(?ts)
4	tco:teacher(?t)^tco:livesIn(?t,?livenv)^tco:LivingEnvironment(?livenv)^tco:is-a(?livenv,?env) ^tco:environment(?env)^tco:hasType(?env,?envtype)^tco:teacher(?ts)^tco:livesIn(?ts,?livenvs) ^tco:LivingEnvironment(?livenvs)^tco:is-a(?livenvs,?envs)^tco:environment(?envs)^tco: hasType(?envs,?envtypes)^swrlb:equal(?envtype,?envtypes) $\Longrightarrow$ sqwrl:select(?ts)
5	tco:teacher(?t)^tco:livesIn(?t,?livenv)^tco:LivingEnvironment(?livenv)^tco:is-a(?livenv,?env) ^tco:environment(?env)^tco:hasCountry(?env,?coun)^owl:country(?coun)^tco:teacher(?ts)^tco: livesIn(?ts,?livenvs)^tco:LivingEnvironment(?livenvs)^tco:is-a(?livenvs,?envs)^tco: environment(?envs)^tco:hasCountry(?envs,?couns)^owl:country(?couns)^swrlb:equal(?coun, ?couns) $\Longrightarrow$ sqwrl:select(?ts)
6	tco:teacher(?t)^tco:worksIn(?t,?inst)^tco:EducationalInstitution(?inst)^tco:evolvesIn(?inst, ?workenv)^tco:WorkingEnvironment(?worknv)^tco:is-a(?workenv,?env)^tco: environment(?env)^tco:hasType(?env,?envtype)^tco:teacher(?ts)^tco:worksIn(?ts, ?insts)^tco:EducationalInstitution(?insts)^tco:evolvesIn(?insts,?workenvs)^tco: WorkingEnvironment(?worknvs)^tco:is-a(?workenvs,?envs)^tco:environment(?envs)^tco: hasType(?envs,?envtypes)^swrlb:equal(?envtype,?envtypes) $\Longrightarrow$ sqwrl:select(?ts)
7	tco:teacher(?t)^tco:worksIn(?t,?inst)^tco:EducationalInstitution(?inst)^tco: hasEducationLevel(?inst,?edulvl)^dcterms:EducationLevel(?edulvl)^tco:teacher(?ts)^tco: worksIn(?ts,?insts)^tco:EducationalInstitution(?insts)^tco:hasEducationLevel(?insts,?edulvls) ^dcterms:EducationLevel(?edulvls)^swrlb:equal(?edulvl,?edulvls) $\Longrightarrow$ sqwrl:select(?ts)
8	tco:teacher(?t)^tco:hasScience(?t,?sci)^modsci:Science(?sci)^tco:teacher(?ts)^tco: hasScience(?ts,?scis)^modsci:Science(?scis)^swrlb:equal(?sci,?scis) $\Longrightarrow$ sqwrl:select(?ts)
–	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^sqrlb:lessthan(?ex,5) $\Longrightarrow$ tco: noviceTeacher(?nt)^rdf:is-a(?t,?nt)
–	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^sqrlb:lessthan(?ex,10)^sqrlb:greaterthan(?ex, 5) $\Longrightarrow$ tco:intermediateTeacher(?it)^rdf:is-a(?t,?it)
–	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^sqrlb:greaterthan(?ex,10) $\Longrightarrow$ tco: expertTeacher(?xt)^rdf:is-a(?t,?xt)

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