Highlights

Recommender Systems for Teachers: the Relation Between Social Ties and Effectiveness of Social-Based Features

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- Social-based recommender systems in education rely on user-generated recommendations, but incentivising users, and teachers in particular, to provide meaningful feedback about the content is a known challenge.
- This study provides strong empirical evidence that social recognition can enhance teachers' responsiveness to feedback requests.
- It also demonstrates, for the first time, the impact of social recommendations from peers on teachers' choice of learning materials
- However, the impact of social rewards on teachers' motivation to provide feedback, and the value they ascribe to peer recommendations, is heterogeneous, and strongly associated with the strength of the ties within the teacher community.

Recommender Systems for Teachers: the Relation Between Social Ties and Effectiveness of Social-Based Features

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ABSTRACT

With hybrid teaching and learning becoming the new educational reality, teachers often face the challenge of searching in open repositories that vary substantially in quality and standards, in order to find suitable learning materials that fit their students' needs and their own pedagogical preferences. Social recommendations, i.e. recommendations from fellow teachers about learning resources, are becoming a popular feature in Open Educational Resource (OER) repositories. However, teachers are often reluctant to provide feedback about resources they used. In addition, very little is known about the value of social recommendations for teachers, namely, whether teachers actually rely on such recommendations when searching for learning resources (LRs). In this research, we studied the behaviour of two science teacher communities – 219 Physics teachers and 118 Chemistry ones – who are using a nation-wide blended-learning environment with an OER repository and social-network features. Following a participatory design process with teachers, we implemented a 'light-weight' recommender system (RS) into this environment, with a social-based incentive mechanism. This RS had two main objectives: first, to allow teachers to share experiences and feedback about LRs they used with the rest of the community; and second, to increase teachers' willingness to provide feedback. Accordingly, we compare two aspects of the influence of this RS on the behaviour of teachers in the two communities: first, its impact on teachers' responsiveness to feedback requests; and second, teachers' use of the social recommendations presented to them in the RS. Results show both the incentivizing power of social rewards and the contribution of social recommendation to teachers' search & select strategies, but also their heterogeneous impact on teachers: while in one community social rewards significantly increased teachers' motivation to provide feedback, and teachers relied on such feedback from peers when selecting learning materials, in the other community social rewards had no effect, consistent with the low value that teachers in this community ascribed to recommendations from peers. We discuss possible factors that may be related to these differences, focusing on the strength of the social ties within the teachers' social network, and suggest implications for the development of OER repositories for teachers.

1. Introduction

Online educational repositories typically offer a wide collection of digital resources that are suitable for different pedagogical needs and individual preferences teachers may have. To aid search & discovery in such collections, open educational resource (OER) repositories typically offer various filtering mechanisms (Downes, 2007). Still, search & discovery within large OER repositories are known challenges, since teachers are generally overwhelmed by the large amount of information returned to them (Diekema and Olsen, 2011).

Various approaches have been examined in the past to address this difficulty, one of which is using recommender systems (RSs) (Manouselis, Drachsler, Vuorikari, Hummel and Koper, 2011). RSs can be defined as software tools that provide suggestions on the most relevant items for a particular user (Dhahri and Khribi, 2021). Among the conceptual approaches for designing RSs is content-based-filtering, which attempts to recommend items similar to other items the

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user liked in the past (Terveen and Hill, 2001), and collaborative-filtering, which attempts to match new items to users, based on the preferences of users who demonstrated similar tastes (Roh, Oh and Han, 2003). Another type of RSs are recommendation-support systems, which serve as tools to support people in sharing recommendations, helping those who produce recommendations and those who look for them (Terveen and Hill, 2001).

RSs that rely on user-generated recommendations have been implemented in a variety of domains, including books, movies, research reports, and news articles. They are especially prominent in the field of e-commerce, where online vendors attempt to provide personalised recommendation of products to their customers (Recker, Walker and Lawless, 2003), and were also implemented in the educational domain (Manouselis et al., 2011).

In 2003, Recker et al. (Recker et al., 2003) designed a RS called "Altered Vista" which was based on teacher and student reviews of learning resources (LRs), and examined its usability in three empirical experiments with teachers and students. Throughout the years since then, such systems have been gaining popularity in the educational field (Dhahri and Khribi, 2021). However, as is the case with other mechanisms that rely on user-generated content, teachers are often reluctant to actively contribute and share opinions and recommendations (Yacobson, Toda, Cristea and Alexandron, 2021), despite the fact that they highly value the opinion of their peers (Recker, Dorward and Nelson, 2004).

Realising the potential value of social recommendations, and with the goal of addressing the above-mentioned 'motivation' challenge, we conducted a participatory design process with Physics teachers who use a nation-wide blended learning environment. Building on the insights gained during this process, we implemented a 'light-weight' RS into the learning environment, in the form of a recommendation panel showing teachers' recommendations about resources they used (see details in section 4.1). This RS had two main objectives: to allow teachers to share experiences and feedback about LRs they used with the rest of the teacher community; and to increase teachers' willingness to provide feedback, by providing social recognition to the contributing teachers.

Accordingly, our first research question was:
(RQ1) Is the social-recognition-based incentive mechanism effective in motivating teachers to contribute time and effort to giving feedback about LRs they used? (hereafter: "the incentive aspect").

In order to examine the incentive aspect, we conducted a study with teachers from two disciplinary teacher communities in Physics and Chemistry, who are active users of a blended learning environment for science teaching. We measured the effect of the RS's implementation on the amount of feedback we received from teachers (see section 4 for details). Results showed heterogeneous effect: While among the physics teachers the recommendation panel had a strong influence on teachers' willingness to provide evaluative feedback, among the chemistry teachers there was no noticeable impact on teachers' behavior.

In addition, when reviewing previous work on the use of RSs to aid teachers, we identified a major gap concerning the evaluation of the RS usefulness from the users' perspective. This gap was already described more than a decade ago in (Manouselis et al., 2011): "[...]a closer look to the current status of their development and evaluation reveals the lack of systematic evaluation studies in the context of real-life applications" (p.18). A very recent systematic literature review of RSs for teachers (Dhahri and Khribi, 2021) indicated that not much has changed in this regard since then. Therefore, in order to address this gap, we wanted to examine not only the RS's social-oriented design on teachers incentives, but also whether teachers are *actually* relying on their peers' recommendations when choosing LRs.

This led us to the formulation of our second research Question:
(RQ2) Do the teachers rely on the social recommendations when searching & selecting learning materials? (hereafter:"the usefulness aspect").

In order to examine the usefulness aspect, we conducted a temporal analysis of the log files documenting teacher actions within the learning environment (see section 5 for details). Again, just like in our study of the incentive aspect, results demonstrated heterogeneous effect, with a strong signal among the physics teachers who relied on their peers' recommendations to a much larger extent then the chemistry teachers when searching and choosing LRs.

These consistent differences between the two communities led us to formulate the third research question:
(RQ3) What are the differences in the relevant characteristics of the two teacher communities (namely, the physics and chemistry ones), which are associated with the observed differences in the incentive and usefulness aspects?)

In order to answer this RQ, we used a mixed method approach that combined qualitative research and Social Network Analysis (SNA). Our findings pointed to a relation between the strength of community ties within the teacher community, and the effectiveness of social-based mechanisms.

The contribution. The contribution of our research is thus threefold: it provides empirical evidence on the positive impact social recognition can have on teachers' willingness to provide feedback regarding LRs they used; it provides, for the first time (to the best of our knowledge), strong empirical evidence for the impact of social recommendations on teachers' choice of learning materials; and it provides insights regarding the relationship between the strength of community ties and the effectiveness of social-based incentive mechanisms among teachers.

2. Literature Review

2.1. Recommender Systems for Teachers

Recommender systems are software tools providing suggestions for items to be of use to a user (Ricci, Rokach and Shapira, 2011). RSs are primarily directed towards individuals who lack sufficient personal experience or competence to evaluate the potentially overwhelming number of alternative items that are presented to them (Klašnja-Milićević, Ivanović and Nanopoulos, 2015). In the field of education, these systems are aimed at aiding learners, teachers and other stakeholders in coping with information overload and helping them make better choices, by informing them about items that might be of interest to them (such as web pages, papers, learning materials, courses, discussion groups, pedagogical patterns and others). RSs have been applied in the educational field since more than two decades ago, and have gained increasing popularity during recent years (Dhahri and Khribi, 2021). Although most of the research regarding the use of RSs in education focuses on RSs for learners (Klašnja-Milićević et al., 2015), there is a growing body of work dealing with RSs for teachers (Dhahri and Khribi, 2021).

However, as noted previously, studies concerning the use of RS in the field of education lack evaluation of usefulness from a users' perspective, especially for teachers (Dhahri and Khribi, 2021) (In fact, it is not rare for studies on educational RSs to not include any sort of evaluation of the system's usefulness). For example, (Leacock, Richards and Nesbit, 2004; Nesbit, Li and Leacock, 2006; Sebbaq, El Faddouli and Bennani, 2020) developed and implemented an RS and conducted initial experiments aimed at improving it, but did not perform an evaluation of its usefulness in real teaching situations. Other studies, such as (Farzan and Brusilovsky, 2011) and (Yacobson et al., 2021), which focused on the question of how to motivate teachers to contribute evaluative meta-data to RSs, did not examine the actual usefulness of these social recommendations to teachers' search & discovery process. Fazeli, Drachsler, Brouns and Sloep (2014) addressed the problem of sparsity (not enough comments and reviews) that hinders educational RSs, and suggested that relying on parameters of social trust when measuring similarity between users could help overcome this problem. But again, their study did not include an evaluation of the systems' usefulness for the teachers.

More common in past research were evaluations that were based on internal metrics, such as precision of recommendations, latency, etc. For example, (Hanna, Abhari and Ferworn, 2017) measured the correlation between user ratings and textual comments regarding LRs in MERLOT, a peer-reviewed repository of educational resources. Another example is the evaluation of the recommender system in (Brusilovsky, Cassel, Delcambre, Fox, Furuta, Garcia, Shipman III and Yudelson, 2010), which concentrated on system-centric metrics, and did not include actual users (teachers and students), but rather conducted an experiment with simulated learners who submit requests for recommendations. However, as was noted by (Karga and Satratzemi, 2018), meeting system-centric metrics does not always correlate with users' satisfaction.

Other studies examined teachers' satisfaction with different aspects of the RS, such as the relevance of the recommendations provided by the system, its interface, or their intention of continuing using the system in the future (Cobos, Rodriguez, Rivera, Betancourt, Mendoza, León and Herrera-Viedma, 2013; Karga and Satratzemi, 2018; Recker et al., 2003). However, the above mentioned studies used surveys and questionnaires, which rely on subjective information. A known issue with this method of evaluation is that there is often a substantial difference between teachers' self-proclaimed attitudes and their actual behaviour (Li, Baker and Warschauer, 2020).

To the best of our knowledge, the only studies that did try to address this problem and actually measured the effect of recommendations on teachers' selection of LRs in real settings, were those of Shelton, Duffin, Wang and Ball (2010), Abramovich and Schunn (2012) and Abramovich, Schunn and Correnti (2013). In (Shelton et al., 2010), logs containing data about teachers' clicks on an educational website ('*Folksemantic*') aimed at supporting teachers in their search for LRs, were analyzed in order to evaluate the system's usefulness. They found that 11% of the recommendations appearing in the website were clicked on. However, clicking on a recommendation does not mean that the teacher indeed found the recommended LR suitable for their needs. Even the authors acknowledge that: “Additional research is needed to understand why people are exploring recommendations and how satisfied they are with recommendations once they have visited recommended resources.” (page 2869). In (Abramovich and Schunn, 2012), the authors studied correlations between evaluative meta-data (e.g. number of ratings of a resource, average rating of a resource, number of comments, etc.) and teachers’ selection of LRs in ‘Teachers Pay Teachers’ - an online marketplace, where teachers can buy and sell original educational materials. They found that the number of times a resource had been rated was more indicative of the probability of a resource being downloaded, than its average rating. In a follow-up research, Abramovich et al. (Abramovich et al., 2013) explored correlations between different types of semantic information and teachers’ selection of LRs in TFANet, a website that supports the exchange of learning resources. They studied the effects of semantic information, such as evaluative meta-data, the type of file that the resource contains, the date in which the resource was uploaded into the system, and more, and calculated to what extent this information predicted the number of times a resource was downloaded by teachers. Their findings confirmed those of their previous study: resources with a higher number of low ratings were downloaded more than resources with a lower number of high ratings. However, as the researchers stated themselves, these correlations could be a result of popular resources receiving more ratings, simply because more teachers used them, and that a temporal analysis is needed in order to establish a causal link.

Overall, despite the considerable body of research conducted on RSs for teachers, and their popularity, there is very little empirical evidence on their actual usefulness in real-life settings (rather than in lab experiments or using internal measures)(Dhahri and Khribi, 2021). *To address this gap, a main goal of the present study is evaluating teachers’ actual use of a social-based RS.*

2.2. Social Recognition

Social recognition is defined as “attitudes and practices by which individuals or social groups are affirmed in certain of their qualities” (Honneth, 2002). In his book “The Struggle for Recognition” (Honneth, 1996), Honneth claims that recognition plays an essential role not only in realising people’s own abilities and skills, but also in facilitating social interaction. All humans seek recognition to build self-confidence, self-respect, and self-esteem; a lack of recognition can lead to depression and illness, or hinder the development of individual skills.

Empirical studies aimed at examining the influence of social recognition on human behaviour found that it can be a strong motivator for improvement in worker performance (Gauri, Jamison, Mazar and Ozier, 2021; Kosfeld and Neckermann, 2011); encourage people to volunteer for low-promotability tasks (Banerjee and Mustafi, 2020); increase engagement in physical exercise (Portela-Pino, López-Castedo, Martínez-Patiño, Valverde-Esteve and Domínguez-Alonso, 2020; Hallmann and Breuer, 2014); promote the emotional well-being of disabled individuals (Danermark and Möller, 2008); encourage users in online communities to share materials that other can reuse (Kim, Kim, Jeon, Jun and Kim, 2016); enhance self-confidence of people who lack social recognition in real-life situations, to be active in online forums or communities (Helm, Möller, Mauroner and Conrad, 2013); influence the sense of autonomy, and as a result the over-all satisfaction from life and work (Renger, Renger, Miché and Simon, 2017).

Regarding the effect of social recognition in the field of education, a study conducted almost a century ago (Hardy, 1937), examined the relations between social recognition and development in elementary school children, also taking into account factors such as number of siblings, gender, marital situation of parents, etc. Results showed that children mentioned as ‘best liked companions’ by at least 20 per cent of their schoolmates, and who came from the same socio-economic level as most of the group, tended to rank above the average of the group in every aspect of development examined. Other studies have shown that social recognition can promote students’ interest in STEM studies (Jackson, Leal, Zambrano and Thoman, 2019), especially for women (Gallus and Heikensten, 2020; Aduragba, Yu, Cristea, Hardey and Black, 2020; Yu, Aduragba, Sun, Black, Stewart, Shi and Cristea, 2020), enhance immigrant students’ participation in school activities (Sirlopú and Renger, 2020), and encourage students to pursue higher education or scientific careers (Thistlethwaite, 1959). Social recognition and interaction with peers was also found to be related to higher interest of students in classes (Thoman, Sansone, Fraughton and Pasupathi, 2012). With regard to teachers, social recognition is a vital need for teachers, and can foster improved performance for teachers and feeling of solidarity with the teacher community (Huttunen and Heikkinen, 2004). It can increase collaboration amongst teachers (Henning Loeb, 2016), promote satisfaction of higher-education faculty members from their work (Amarasena, Ajward and Ahasanul Haque, 2015), and raise teachers’ self confidence (Mangaleswarasharma, 2017). Incentivising teachers and school principals using social recognition has also been found to improve students’ performance (Arora, Fazlul, Musaddiq and Vats, 2022).

However, while recognition can create positive outcomes in the educational domain, in certain contexts it can also have a negative and unwanted effect on human behaviour. For example, Salganik et al. (2008) conducted an experiment showing that users of a social website for downloading songs were more influenced by the song's perceived popularity than by its true appeal, in their choice of what songs to download (Salganik and Watts, 2008). This process is similar to that described in (Abramovich and Schunn, 2012; Abramovich et al., 2013)(see previous section), where users choose LRs according to the number of comments they received rather than their actual quality. These findings suggest that social preferences and recognition given by a community can sometimes lead to poor choice of content by community members. In higher education, lecturers seeking social recognition and prestige can conform to institutional demands, thus reducing their autonomy (Arias et al., 2009). The need for recognition may also produce a negative impact on the school community: when extrinsic rewards (in the form of social recognition) are present, individuals are less likely to depend on their intrinsic motivation to get something done. This can produce a harmful environment where individuals only perform when there is a reward attached to the assignment (Movsessian, 2018). In addition, while individuals receive benefits such as increased confidence, one's sense of community may be diminished. When individuals receive acknowledgement, those who did not receive the praise may be left out or feel invisible because they were not recognized for their work (Movsessian, 2018). School-based recognition and individual recognition from supervisors has also been shown to produce feelings of competition and jealousy (Dinham and Scott, 2002).

The present study goes beyond previous work, by examining the hetrogenous effect of social rewards, focusing on the relationship between community characteristics and the impact of social recognition on teachers' motivation.

2.3. Social Network Analysis for studying teacher communities

Social networks are defined as groups of nodes (or members) that are tied by one or more types of relations (Yassine, Kadry and Sicilia, 2022). Social Network Analysis (SNA) provides a rich set of theoretical constructs and visualization techniques to think about complex social networks in concrete, measurable terms. Thus, SNA moves beyond characteristics of the individuals to focus on characteristics of the relationships in which those individuals are embedded (Polizzi, Ofem, Coyle, Lundquist and Rushton, 2019). The basic premise of SNA is that the different patterns of social ties between group members can have a considerable effect on those members' behaviour (Freeman, 2004). Therefore, researchers who apply SNA methods wish to uncover and study these patterns and their implications on groups as a whole and on individual members.

Some of the main attributes being used to characterise social networks are (Shu and Gu, 2018):

- *Size*, i.e the number of members included in the network.
- *Density*, which measures how many ties or connections exist between members, compared to how many connections or ties between members are theoretically possible. Evaluating the network's density can help us understand how connected the network is in comparison with how connected it might be.
- *Tolerance*, which is the proportion of all connected members to the size of the entire community. Tolerance can help identify whether the network includes all the individuals in a certain population, or whether there is a significant number of isolated members.
- *Average degree*, which is the average number of connections to other members that each member in the community has.
- *Diameter*, which is the maximum distance between two members of the network.

SNA has been applied in various domains, such as occupational mobility (Toubøl and Larsen, 2017), relations between urbanization and ecology (Guan, Dong, Shen, Gao and Chen, 2022), counter-terrorism measures (Olajide and Adeshakin, 2016), community decision-making (Liao, Li and Tang, 2021), social support in workplaces (Froehlich and Gegenfurtner, 2019), group problem-solving (Wu and Nian, 2021), coalition formation on the basis of shared belief systems (Ingold, 2011), marketing (Litterio, Nantes, Larrosa and Gómez, 2017), computer-mediated communication (Thoms, Eryilmaz, Dubin, Hernandez and Colon-Cerezo, 2020), and more. In education, SNA was applied for various purposes. In (Martínez, Dimitriadis, Rubia, Gómez, Garrachón and Marcos, 2002), the authors tried to encourage collaboration among students participating in a university engineering course, by introducing group activities into the course. They then used SNA (alongside other methods) in order to analyse the influence of their intervention on the social structures of the learning group. In (Aviv, Erlich, Ravid and Geva, 2003), SNA was used to investigate the influence of the design of two Asynchronous Learning Networks (ALNs) on the social structures and quality of learning in these two ALNs. Since these early studies, there has been an exponential growth in research in this field (Baker-Doyle and Yoon, 2020). This body of research consists of papers examining the use of SNA to study the effects of social relations both on learners and on teachers. For instance, Dado and Bodemer (2017) conducted a systematic review of 89 papers on the topic of SNA use in the field of computer-supported collaborative learning. All papers included in this review used SNA to investigate social relations between *learners*. In Dawson, Bakharia, Heathcote et al. (2010), a monitoring/diagnostic tool, with SNA and visualization features for analyzing discussion forums and providing real time analytics on the evolving social patterns in a learning group. Chang, Lin and Wu (2010) studied how different ways to organise peer teams affect communications among team members, as well as the teacher's ability to manage the teams. However, SNA was proven effective also for studying social relations within *teacher* communities. For example, in K-12 settings, a context more similar to the one studied in the present research, (Moolenaar, Sleegers and Daly, 2012), which was conducted in 53 dutch elementary schools, and centered on examining the relationship between teacher collaboration and student achievement, using SNA methods. Most related to our work in terms of context and analysis is the work of Scherz, Salman, Alexandron and Shwartz (2022), who used SNA to study professional knowledge development and social interactions within teacher communities, as derived from its WhatsApp group discourse.

SNA has also proven to be an effective means for analysing e-learning environments, since SNA methods can deal efficiently with the large amount of data on e-learning systems, and the quantitative measures and graphical representations of SNA can help teachers understand social and communicational patterns in online communities of students and of teachers (Cela, Sicilia and Sánchez, 2015). Therefore, it is not surprising that indeed in recent years there has been considerable use of SNA in the field of online learning (Yassine et al., 2022).

Altogether, this considerable body of research demonstrates the effectiveness of SNA as a tool to study social relations within communities. Therefore, in this research we applied SNA methods to measure and describe online social networks of teachers who use a blended-learning environment that include social network features. We then went on to describe the relations between characteristics of teachers' social networks and the effectiveness of social-based features embedded into these learning environments.

3. Methodology

3.1. Research Overview

In this research, we conducted three studies to answer the three RQs.

- *Study 1* aimed at answering RQ1 about the incentive aspect. In this study we measured the impact of a social-based incentive mechanism on teachers' motivation to provide evaluative feedback.
- *Study 2* aimed at answering RQ2 about the usefulness aspect. In this study we analysed log files containing teachers' actions in the learning environment to examine teachers' use of social recommendations in their search process for LRs.
- *Study 3* aimed at answering RQ3 about the differences between the two teacher communities (Physics and Chemistry) who participated in this research. In this study, we conducted interviews with teachers and used SNA to analyse the strength of the social ties in the online social networks of these two communities.

3.2. The Learning Environment

The learning environment in which we conducted this research is called PeTeL (**Pe**rsonalized **Te**aching and **L**earning; 'Raspberry' in Hebrew). PeTeL is both a shared repository of OERs, and an LMS that also includes social network features and learning analytics tools. It is developed within the Department of Science Teaching at the Weizmann Institute of Science (WIS), with the goal of providing a blended learning environment for personalised instruction in the science classroom. PeTeL is divided into separate modules for each subject matter: Biology, Chemistry and Physics, and is freely available to science teachers on a national scale. It is implemented on top of the Moodle learning management system. All teachers actions in the system, such as logging into the system, navigating to a course page, searching or downloading activities, adding LRs to the repository or providing feedback on existing ones, are logged by the learning environment.

3.2.1. OER Repository in PeTeL

The different modules in PeTeL contain an OER repository with a large variety of interactive activities. These activities are created either by the content development team or by the teachers themselves. A teacher can search the repository for an activity according to different criteria, such as subject matter, level of difficulty, duration, technical requirements (e.g. projector or mobile devices), nature of the activity (e.g. diagnostic questionnaire, interactive task, home assignment, etc.) and more. After choosing an activity, teachers can download the activity into their own personal environment inside PeTeL, and use it during the lesson or as homework. Various teacher dashboards that are available to the teachers provide analytics on student behaviour and performance.

3.2.2. Social Network in PeTeL

PeTeL has a built-in social network that allows teachers to share resources, lesson plans, and even entire teaching sequences with each other (see Figure 1). A teacher can request to be either a 'follower' or a 'colleague' of another teacher. A 'follower' receives notifications on new resources that the followee added to his/her personal environment, and request access to them, while a 'colleague' is a bi-directional relation that provides access to all course materials.

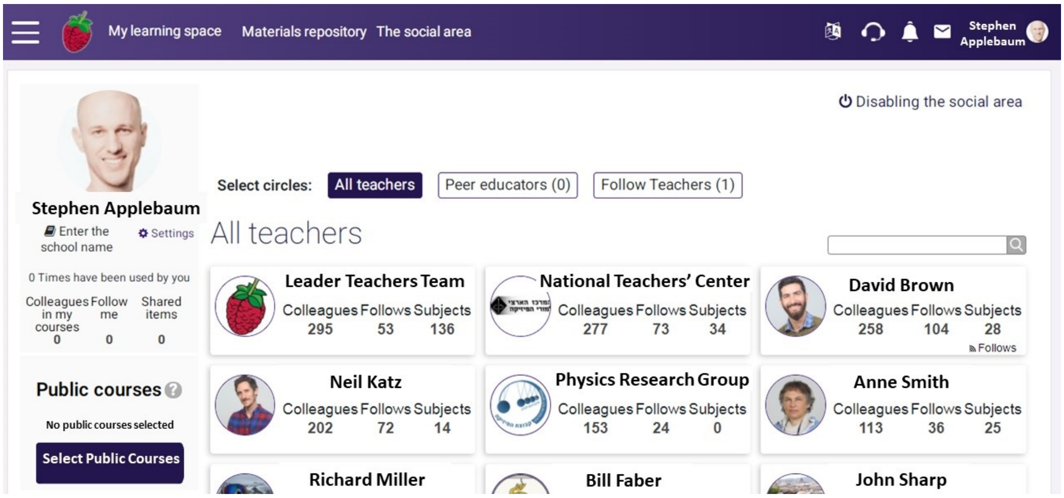

Figure 1: Social Network in PeTeL (real names were replaced to preserve teacher privacy)

3.2.3. Feedback Mechanism in PeTeL

After using an activity in their class, the teachers are presented with a 'pop-up' window requesting them to provide evaluative feedback concerning the resource they used (see Figure 2).

The teachers can either fill in the pop-up survey, postpone filling in to a later date, or cancel it. This feedback mechanism was initially activated in PeTeL during the 2019 – 2020 school year. However, teachers' cooperation was relatively low, and their response rate to the feedback requests during this first year was below 3%. Recognising the importance of social recommendations in aiding teachers in their process of searching and choosing LRs, we marked the issue of increasing the response rate as a major challenge that should be addressed.

3.3. Research Population

PeTeL is currently in use by approximately 1000 STEM teachers in Israel, mainly from two disciplinary teacher communities – physics and chemistry. Since the physics component of PeTeL exists for several years, while the chemistry component is more recent, the amount of active teachers in the physics community is larger than in the chemistry one. We define a teacher as 'active' if that teacher downloaded at least one LR from the environment and administered it to his/her students, and omitted from our analysis teachers who have registered to the system but did not use it. This resulted in a research sample of 219 physics teachers and 118 chemistry ones. Sixteen teachers, eight from each group, participated in the qualitative part of this research, which included semi-structured interviews.

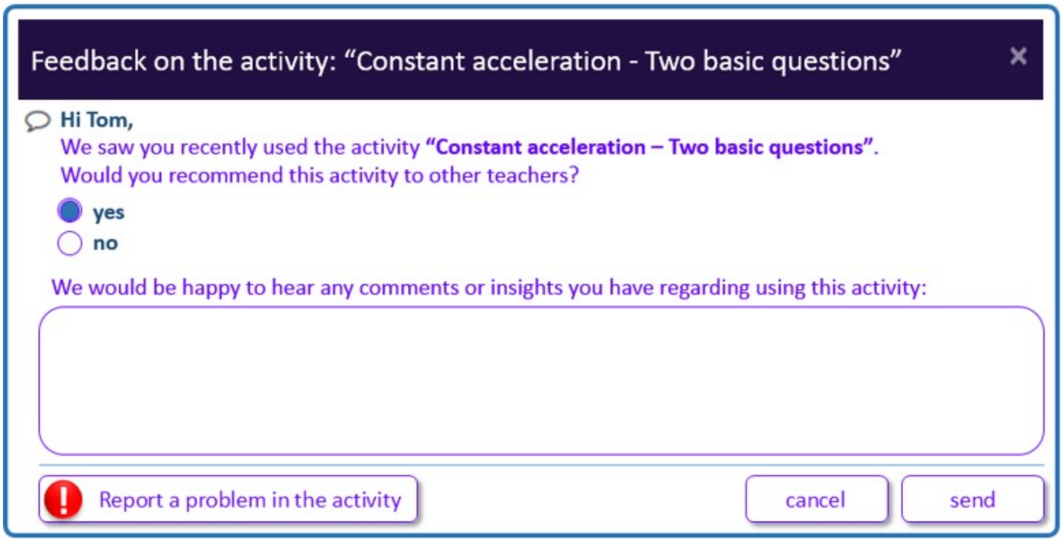

Figure 2: Feedback Mechanism in PeTeL (introduced 2019-2020)

4. Study 1: Social Reward as an Incentive Mechanism

In this study, our objective was to answer RQ1 concerning the incentive aspect. Following the results from initial work we conducted with teachers using PeTeL (Yacobson et al., 2021), we focused on the idea of using social-based incentive mechanisms, and examined whether providing social recognition to teachers can encourage them to provide feedback.

In order to answer this question, we first worked with the Physics teachers using PeTeL, and then expanded our research to the Chemistry module.

4.1. Physics Teachers' Response to Social Rewards

This study took place during the 2020-2021 school year, and consisted of two stages: in the first stage, we conducted a participatory design process with Physics teachers, aimed at understanding which incentive elements are most likely to influence teachers' behaviour. In the second stage, based on our findings from the participatory design process, we implemented a new recommendation panel into the Physics module in PeTeL.

4.1.1. Participatory Design Process

During a workshop held at the annual PeTeL conference, we presented 17 physics teachers with five mock-ups of different incentive elements (such as a leader board, virtual badges and more), based on a novel methodology (Toda, Oliveira, Klock, Palomino, Pimenta, Bittencourt, Shi, Gasparini, Isotani and Cristea, 2019). We then asked them to rank these elements according to how much they believed each element would contribute to teachers' willingness to give feedback. In addition, we provided teachers with a few open ended questions and held a group discussion in which they were asked to express their opinion about the feedback mechanism in PeTeL and raise ideas on how to improve it. Our main conclusions from this first stage of the experiment were: (a) Teachers need to have a feeling of 'impact', i.e., they need to feel that their feedback is meaningful, that it is taken seriously, and that it is contributing to the rest of the teacher community and to the learning environment; and (b) Social recognition matters, meaning that teachers not only want to feel that they are contributing, but also to be recognised by their peers for their effort and contribution. For details regarding this stage, see (Yacobson et al., 2021).

4.1.2. Implementation of Recommendation Panel

In light of these findings, in the second stage of the study, we implemented a recommendation panel into the Physics module in PeTeL (see Figure 3).

This panel is located on the main page of the learning environment, and presents teachers' reviews about LRs they used in their classrooms. Each time a teacher reviews an LR they used in class, the recommendation panel is updated,

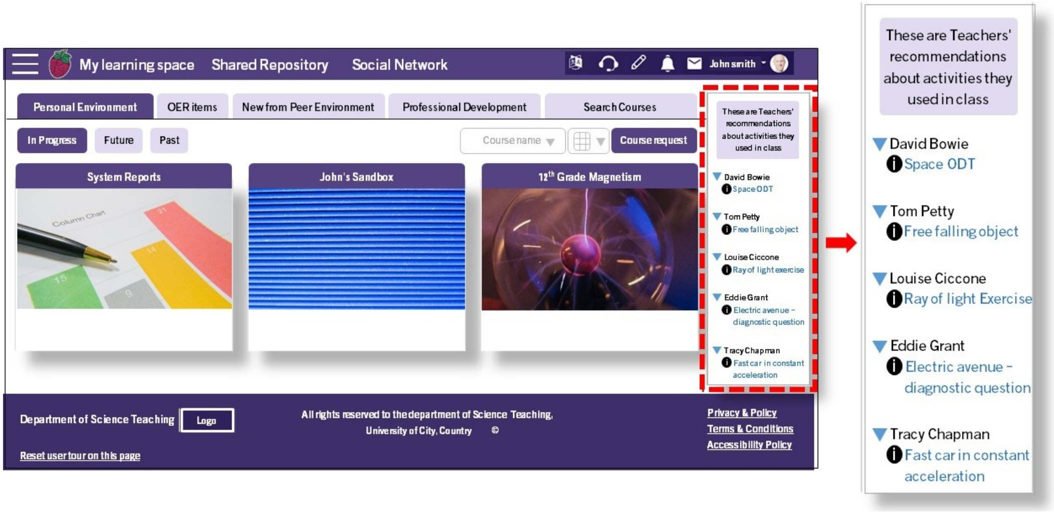

Figure 3: Social recommendation panel, introduced in PeTeL 2020 (real names replaced for privacy protection)

presenting the new feedback at the top of the panel. Each new entry to the recommendation panel contains both the name of the recommending teacher, and the title of the LR that has been recommended. When hovering with the mouse over a recommendation, a mouse-over text appears, with the details of the recommendation. All of the recommendations appearing in the recommendation panel are 'linked', meaning that teachers can click on a recommendation and be redirected to the LR repository, so they can download the recommended LR to their own course or class. This element addresses teachers' needs found during the participatory design process: both their need to have a feeling of impact, that their feedback is actually helpful to the entire teacher community, and their need for social recognition.

After the implementation of the recommendation panel in the Physics module in PeTeL, we monitored teachers' reviews about LRs.

4.1.3. Results

During the 7 months after the implementation of the recommendation panel, we received 114 reviews from teachers, which is an average of 16.2 reviews per month. **This constituted a X2.7 increase in comparison to the previous year**, before the implementation of the recommendation panel.

To examine whether the increase was merely the result of teachers using more LRs during this period, and therefore receiving more feedback requests, we also checked the response rate in each year, i.e. the percentage of feedback requests that were answered by the teachers. During the year before the implementation of the recommendation panel, teachers used 2,372 LRs, and we received 61 reviews, resulting in a 2.6% response rate. During the 7 months after the implementation, teachers used 1,888 LRs, and we received 114 reviews, resulting in a 6% response rate. **This constituted a X2.3 increase in comparison to the previous year**. A one-tailed proportion test showed that this increase is statistically significant ($z=5.66$, $p<0.001$).

4.2. Chemistry Teachers' Response to Social Rewards

Encouraged by our success in the Physics module, we decided to expand our research to an additional module in PeTeL: the Chemistry module. This module exists in PeTeL since 2019, but up until now did not include a feedback collection mechanism requesting teachers to review LRs they used. Therefore, during the 2021-2022 school year, we implemented the feedback mechanism into the Chemistry module, completely identical to that of the Physics module.

4.2.1. A/B testing experiment

In order to test the recommendation panel's impact on teachers' willingness to provide feedback, we decided to use a different methodology than the one used in the Physics module. Since unlike the Physics module, we did not have data regarding previous years (given that a feedback mechanism did not exist in the Chemistry module in previous years), we decided to conduct an A/B testing experiment: the 118 active teachers in the Chemistry module were randomly

Table 1
Teachers' Clicks and Downloads (Teachers' names were anonymised); "click & download" event identified, in bold

	Teacher name	Resource id	Event Type	Time
1	David Brown	417	download	2020-08-19 21:06:15
2	John Smith	1085	download	2020-08-19 21:15:22
3	Jane Doe	190	click on recommendation	2020-08-19 22:41:58
4	**Kyle Martin**	**2316**	**click on recommendation**	**2020-08-20 10:32:17**
5	**Kyle Martin**	**2316**	**download**	**2020-08-20 10:34:21**
6	John Smith	606	download	2020-08-21 16:53:12

divided into an experimental group and a control group (59 teachers in each group). Teachers in both groups received feedback requests about every LR they used in class, but the teachers in the experimental group were presented with the recommendation panel, whereas the teachers in the control group were not. We then compared the number of reviews we received from each group.

4.2.2. Results

Control group: out of the 59 teachers in the control group, 34 teachers (58%) filled in 64 reviews. The response rate for this group was 15% (64 reviews out of 428 feedback requests).

Experimental group: out of the 59 teachers in the experiment group, 24 teachers (41%) filled in 61 reviews. The response rate for this group was 16.3% (61 reviews out of 374 feedback requests).

A one-tailed proportion test showed that the difference between the response rate of the two groups was **not** statistically significant ($z=0.528$, $p=0.298 > 0.05$).

4.3. Summary of results from the first study

In this study, our goal was to examine whether social recognition can increase teachers' willingness to provide feedback regarding LRs they used. To that end, we implemented a 'light-weight' RS in the form of a recommendation panel into two modules in PeTeL: the Physics module and the Chemistry module. The rationale was that the visibility of the feedback to the entire community would serve as a social reward and incentivise teachers to provide more feedback. Results in the two modules were considerably different: in the Physics module there was a significant increase in the number of reviews received from teachers following the implementation of the panel, whereas results from the A/B testing experiment in the Chemistry module showed no impact whatsoever of the panel on teachers' responsiveness to feedback requests.

5. Study 2: Teachers' Use of Social Recommendations

After examining the influence of the recommendation panel on teachers' responsiveness to feedback requests, a subsequent question emerged regarding the usefulness of these recommendations for teachers. Our goal in the second study was to examine this aspect (as formulated in RQ2), and see whether teachers are actually using the social recommendations in the panel to find LRs suitable to their needs.

To that end, we conducted a temporal analysis of teachers' actions, and in addition compared the number of downloads of LRs before and after these were recommended.

5.1. Methodology

5.1.1. Analysis of Teachers' Actions Log File

In order to answer RQ2, we first analysed teachers' activity in the system, stored in log files containing data about their interaction with the platform, and intersected these logged activities with the information concerning the recommendation that appeared on the recommendation panel. For example, Table 1 presents sample information on two types of teacher interaction: clicking on a recommendation in the panel (which opens the body of the recommendation and provides a link to the resource), and downloading a resource from the repository to the teacher's personal teaching space.

In order to identify occurrences in which a teacher followed a recommendation and downloaded the recommended LR, we looked for events in which teachers clicked on a recommendation about an LR appearing in the recommendation panel, and shortly afterwards downloaded that resource to their own environment. Specifically, we define such "click & download" events as a click on a recommendation, followed by a download of the recommended LR, which took place no longer than 24 hours after the recommendation of the downloaded resource. The reasoning behind it is that any longer delay between the two actions can not be reliably considered to be causally relating the two actions. An example of such an event can be seen in rows 4 and 5 in Table 1. We considered such events as evidence that the teacher used the recommendation to find a learning resource suitable for their needs.

5.1.2. Comparison of Downloads Before and After Recommendation

In addition to the temporal analysis of teachers' actions, we examined whether there was an increase in the number of times LRs were downloaded following them being recommended, using two types of quantitative analysis: first, we conducted a hypothesis test, by comparing, for each LR that was recommended, the number of times it was downloaded during the week before and the week after it was recommended. Second, we examined the global pattern received from accumulating the amount of weekly downloads per resource during a six week period – three weeks before the recommendation and three weeks after it. The reason for choosing 3 weeks before and after the recommendation, was that most teachers follow a similar order and timing in which they teach the different subjects. Therefore, examining a longer period of time would probably result in adding 'noise' to the data.

5.2. Results - Physics Module

The log file containing the detailed account of Physics teachers' clicks on recommendations and downloads of resources contained 7,099 events: 682 were clicks on recommendations and 6,417 were downloads of resources. We found 101 "click & download" events (as defined in section 5.1), which took place during 8 months (from April 2021 to December 2021), resulting in an average of 12.6 events per month. These events were generated by 50 different teachers, constituting approx. 23% of the active Physics teachers in PeTeL.

In the hypothesis test, 81 resources that were recommended by the teachers were examined. These resources were downloaded a total of 132 times during the week before they were recommended, and 178 times during the week after they were recommended. The number of downloads before and after the recommendation were not normally distributed. Therefore we conducted a one-tailed Wilcoxon signed-rank test that rejected the null hypothesis that the number of downloads before the recommendation is not statistically significantly different from the ones after the recommendation ($n=81$, $Z=1.955$, $p=0.025$). Thus, we accepted the alternative hypothesis that there was a statistically significant increase in the amount of downloads following the recommendation.

Next, when examining the global pattern, by accumulating the amount of weekly downloads in the three weeks before and after the recommendation, there is an evident 'peak' in the number of downloads in the week following the recommendation (see Figure 4).

We note that the steep decline in the number of downloads in the two following weeks could be a result of other resources being recommended, thus 'pushing' the recommendation about a certain resource outside of the recommendation panel (the recommendation panel contained only the five most recent recommendations, at any given time). Another explanation could be that most teachers, as said, follow a similar schedule and order of subjects, when they teach. Therefore, a recommendation regarding a certain resource is relevant only for a short period of time, during which the majority of teachers are teaching the subject that resource deals with.

5.3. Results - Chemistry Module

The log file containing the detailed account of Chemistry teachers' clicks on recommendations and downloads of resources contained 2,046 events: 103 were clicks on recommendations and 1,943 were downloads of resources. We found 13 "click & download" events (as defined in section 5.1), which took place during 10 months (from September 2021 until June 2022), resulting in an average of 1.3 events per month. These events were generated by 7 different teachers, constituting approx. 12% of the active Chemistry teachers in the experiment group.

When comparing the number of downloads before and after the recommendation, we found 81 resources that were recommended. These resources were downloaded a total of 112 times during the week before the recommendation, and only 80 times during the week after the recommendation. This means that the observed change is actually a decrease in the number of downloads after the recommendation.

Next, when examining the global pattern, by accumulating the amount of weekly downloads in the three weeks before and after the recommendation, this time there was an evident 'peak' in the number of downloads in the week BEFORE the recommendation (see Figure 5).

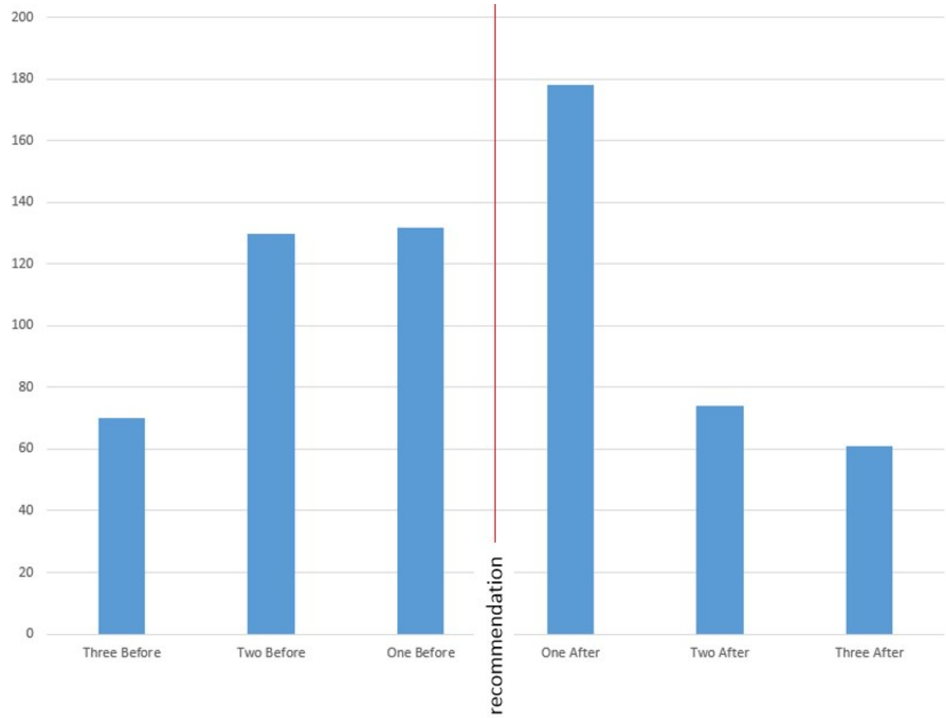

Figure 4: Physics: Downloads 3 weeks *before* and *after* a recommendation

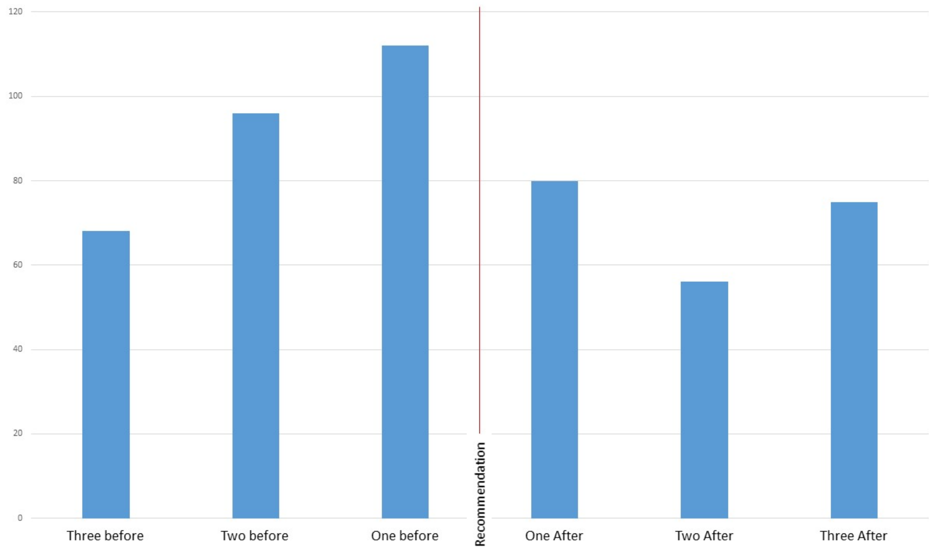

Figure 5: Chemistry: Downloads 3 weeks *before* and *after* a recommendation

5.4. Summary of results from the second study

The goal of this second study was to examine whether teachers actually value the social recommendations, by looking on the impact on their choice of which LRs to select and download to their course. Consistent with the first study, the results showed a heterogeneous effect: in the physics module we observed an evident, statistically significant impact of the social recommendations on teachers choice of LRs, while in the chemistry module no such impact was observed.

6. Study 3: Relations Between Social Ties and Effectiveness of Social-Based Features

As described earlier in the introduction of this paper, after witnessing the notable differences between the two teacher communities participating in this research, both in terms of the impact of the social rewards on teachers' willingness to provide feedback and in their use of the social recommendations, we decided to examine what are the factors that might be related to these differences (RQ3).

In order to answer this question, we first conducted an in-depth qualitative study, via 16 interviews with Physics and Chemistry teachers. Analysis of teachers' responses during these interviews suggested that the social-based incentive mechanism works differently in these two communities due to differences in the strength of the social ties within them. We therefore continued to examine the structure and strength of community ties for these two specific communities, by using Social Network Analysis (SNA) methods. These two completing analyses are reported below.

6.1. Qualitative Research

6.1.1. Research population

The research population for the qualitative part of our research consisted of 16 teachers who were active users of PeTeL (described in section 3.3). The teachers selected for the in-depth interviews were chosen with the purpose of representing a broad variety of backgrounds in terms of their teaching experience and experience in working with PeTeL, in terms of gender, and in terms of technological orientation and proficiency. The groups were also chosen to be of the same size. As a result, eight Physics teachers and eight Chemistry teachers took part in the interviews. In the Physics group there were six men and two women (this is due to the fact that the Physics teacher community is predominantly male). The Physics teachers' teaching experience was very varied, ranging between 2 - 35 years (M=11.9, SD=9.8) and their experience in using PeTeL ranged between 2 - 4 years (M=3, SD=1.3). In the Chemistry group, there were seven women and one man (this is due to the fact that the Physics teacher community is predominantly female). The Chemistry teachers' teaching experience ranged between 3 - 24 years (M=14.1, SD=7.7) and their experience in using PeTeL ranged between 1 - 4 (M=2.5, SD=1). The maximum possible experience in using PeTeL was 4 years for both teacher communities.

6.1.2. Methodology

The interviews were semi-structured, consisting of five questions: (1) Did you notice the recommendation panel? (2) Do you feel it had any effect on your willingness to give feedback on LRs you used? (3) If you gave feedback, what motivated you to do so? (4) Did you download a LR following a recommendation appearing in the panel? (5) If you did, what were the considerations leading you to follow a certain recommendation?

The interviews were 10 - 20 minutes long. They were held through the Zoom application, recorded and transcribed.

6.1.3. Results

Panel's Impact on Willingness to Provide Feedback: All the teachers participating in the interviews, both Physics and Chemistry, acknowledged that they did indeed notice the recommendation panel. Regarding the panel's impact on their willingness to provide feedback, all the teachers (except for one Physics teacher) stated that the panel did not affect their willingness to provide feedback. Only one Physics teacher said that: "Yes, seeing my name in the panel is something that affects me... It also gives you a feeling of a community, of a social network. You see other teachers' names and know what they are currently teaching". However, there was still a difference between the two communities: on top of the aforementioned Physics teacher, an additional Physics teacher said that she herself wasn't affected by the panel, but that perhaps it does have an effect on other teachers. Two other teachers from the Physics group indicated that the panel itself did not contribute to their motivation to provide feedback, but when asked why did they still provide feedback they said that they felt obligated to give back to the community: "I told myself - OK, I used an activity from the shared repository that others put an effort into, so I have to find the time and do this (i.e. - write a review)". These examples show that for at least some of the Physics teachers, there is a strong sense of belonging to a community, rendering the social-based incentive mechanism more effective.

On the other hand, in the Chemistry group, not only did teachers state that the recommendation panel did not increase their motivation to provide feedback, but three of them clearly stated that knowing that their recommendation would be presented to other teachers, actually deterred them from writing a review. One teacher simply said that she didn't want her name to be in the panel. One said she used an LR that she did not like, and felt uncomfortable writing a bad review that would be presented to the rest of the teachers. The third teacher said that because she knew her recommendations would be presented to other teachers through the panel, it made her feel like she had a great responsibility: "...If I write a review and everyone will read it, I don't want to mislead anyone". Two other teachers said that since they don't rely on other teachers' recommendations in order to find LRs, they see no point in providing such recommendations to others: "I don't really think my recommendation will help anyone. Just as other teachers' recommendations aren't something I take into account". Finally, two Chemistry teachers raised the issue that the recommendations presented in the panel were about LRs in a different subject than the one they were currently teaching at that time, rendering the recommendation irrelevant to their needs. This is due to the fact that Chemistry teachers, in contrast to Physics teachers, do not follow a similar order and timing when teaching the different subjects in the curriculum.

Teachers' Use of Recommendations to Find LRs: This part of the interviews was used to triangulate the quantitative data, but also to gain additional insights about teachers' considerations regarding which recommendation to follow. Five of the Physics teachers said they used the recommendation panel at least once to find LRs suitable to their needs, whereas only one of the Chemistry teachers said the same. This is in alignment with the results presented previously in sections 5.2 and 5.3, showing an extensive use of social recommendations by the Physics group in comparison to a very low level of use by the Chemistry teachers. Regarding the considerations leading teachers to follow a certain recommendation: out of the 6 teachers that said they used the panel to find LRs (5 Physics teachers + 1 Chemistry teacher), all of them said they just happened to see a recommendation about a LR in the subject they were looking for. Two of the teachers said they were also influenced by the identity of the recommending teacher: "I see people I know from PeTeL, or from the group of Physics teachers I know, and I say – I know this teacher. Let's see what she wrote. These are teachers I recognise, they are 'celebrities' within the teacher community".

6.1.4. Summary of interviews with teachers

To conclude, in the interviews with the Physics and Chemistry teachers we found that the teachers in the Physics group had a stronger feeling of belonging to a community and obligation to contribute to that community than the Chemistry teachers, which could explain the high effectiveness of the recommendation panel as an incentive mechanism in the Physics module in comparison to the Chemistry module. In light of these findings, we hypothesised that the difference in the strength of community ties in these two communities could be responsible for the differences in the results of studies 1 and 2. To further substantiate this hypothesis, we examined the strength of the community ties as represented in the online-networks of the teacher communities in PeTeL, using SNA methods.

6.2. Social Network Analysis

Following the interviews with the teachers, we examined the strength of social ties of the two communities by analysing the social-networks of these communities inside PeTeL (see section 3.2.2 for a description of PeTeL's social network feature). Our goal in this study was to examine differences in the strength of community ties between the teachers in these two communities.

The analysis was conducted using the open graph visualisation software "Gephi" [1]. In our analysis of the social network, we included only the active teachers that participated in studies 1 and 2. The graphs that represent the online social networks of both communities appear in figure 6 (the Physics teachers' community) and figure 7 (the Chemistry teachers' network).

Each node in the graph represents a teacher. The graph is a directed graph, where edges represent a teacher following another teacher. The size of a node is determined according to the degree of the teacher, meaning the amount of edges going into and out from that node.

Social Network Analysis (SNA) allows us to have a descriptive as well as visual overview of the network structure of the two teacher communities and identify differences between these communities. We summarised the descriptive overview of the two social networks in table 2.

'Out degree' is the number of edges stemming from a certain node, i.e the number of teachers a certain teacher is following. 'In degree' is the number of edges entering a certain node, i.e the number of teachers following that certain teacher. 'Isolated teachers' are teachers who do not follow, and are not followed by, any teacher. 'Tolerance' is the percentage of teachers who are **NOT** isolated, out of the entire teacher population (meaning that they follow at least one other teacher, or at least one other teacher follows them). 'Graph density' is the relation between the existing number of edges in the graph and the maximum possible number of edges. 'Diameter' is the maximum distance (i.e. number of edges) between two teachers.

[1] https://gephi.org/

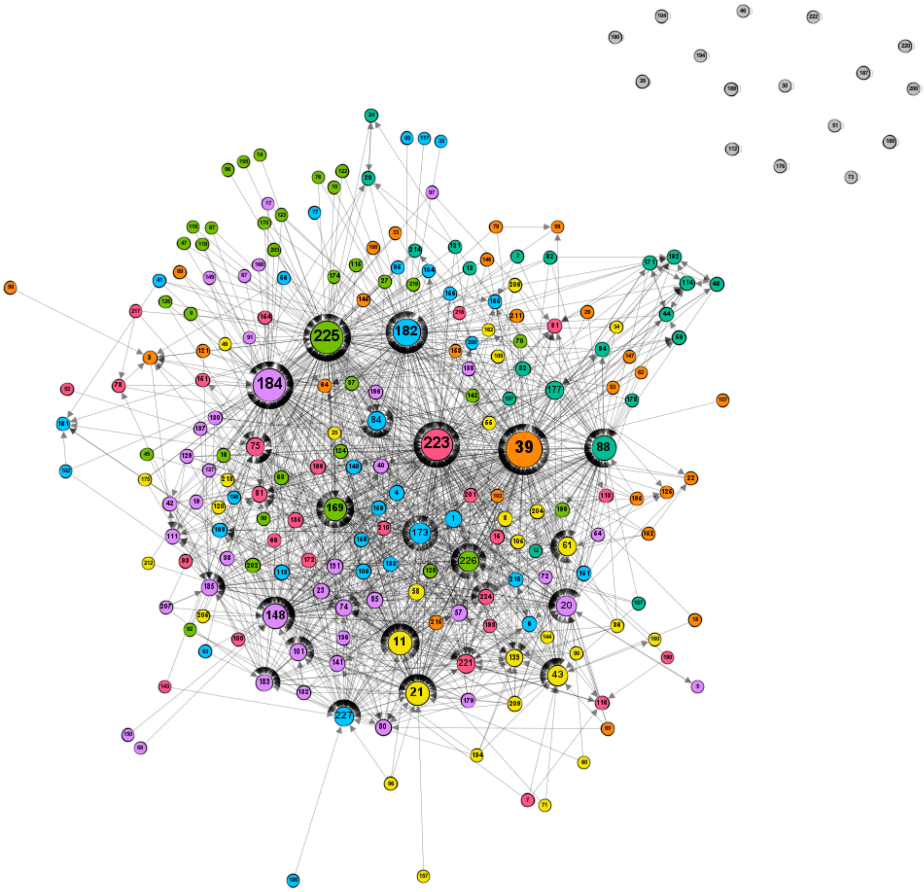

Figure 6: Physics Social Network

Table 2
Social Network Analysis

SNA Metric	Physics	Chemistry
Size (number of teachers)	227	118
Number of edges	1496	386
Average In/Out degree	6.59	3.27
Tolerance	93% (16 isolated teachers)	77% (27 isolated teachers)
Graph density	0.027	0.029
Diameter	7	4

As can be seen, the physics community, which has more members, has a larger number of edges, and a larger diameter. Results also show a higher average in/out degree in the Physics network, indicating stronger social ties between the Physics teachers. A one-tailed t-test showed this difference in degree to be statistically significant ($p=0.001$). In addition, tolerance is significantly higher in the Physics community (93%) in comparison to the Chemistry community (77%), meaning that there are considerably less isolated users in the Physics community.

However, there is one parameter in which the two communities did not differ whatsoever: the graph density, which in both networks is almost identical. The explanation to this fact is the substantial difference in the size of the two networks. The Physics network's size (i.e. the number of active teachers in the network) is almost x2 than the Chemistry

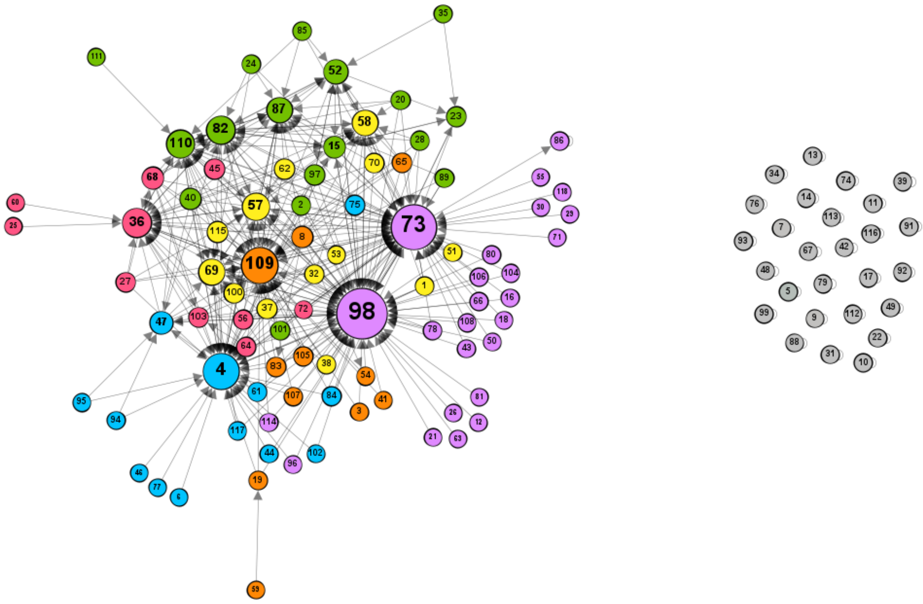

Figure 7: Chemistry Social Network

network's size. The larger the network, the harder it becomes to reach full density (Saqr, Nouri and Jormanainen, 2019). Therefore, similar density in a network twice as large, can actually mean a stronger level of social ties between the teachers in the Physics group.

6.2.1. Summary of SNA of the two communities

The SNA conducted on the two teacher communities revealed that the hypothesis we articulated following the interviews with the teachers – that the Physics teachers' community was characterised by stronger community ties – was indeed correct. The average number of teachers following other teachers was higher in the Physics social network, with a lower number of isolated users in this community.

7. Discussion

7.1. The Incentive Aspect - Social Reward as an Incentive Mechanism

This research examined teachers' use of social recommendations to find online LRs. First, We examined ways in which we can promote and encourage teachers' participation in providing social recommendations, focusing on the impact of social-based incentive mechanisms on their motivation ("the incentive aspect"). To that end, we integrated a 'light-weight' RS in the form of a recommendation panel into a blended-learning environment. The panel presents the names of teachers who reviewed LRs, thus providing them with social recognition for their contribution to the community. The results from our study with the Physics teachers showed a considerable increase in the number of reviews received after the implementation of the recommendation panel, indicating that at least in some cases, social recognition can serve as a powerful tool to raise teachers' responsiveness to feedback requests.

We believe that one of the reasons for the successful impact of the RS on Physics teachers' motivation, is the participatory design process that we conducted with these teachers prior to the implementation of the recommendation panel. This process allowed us to 'tap into' the underlying factors that affect their motivation, and design our incentive mechanism accordingly.

However, we acknowledge the fact that although the social based incentive mechanism proved to be very efficient in the Physics module, it had no evident effect in the Chemistry module. This may be due to the fact that social recognition can also have negative effects and act in undesired ways (Arias et al., 2009; Dinham and Scott, 2002; Movsessian, 2018). In our case, some of the teachers reported in the interviews that they found it intimidating to have their names published to the entire community, making social recognition a *deterring* factor for them when being requested to provide feedback. We believe that in the Physics module, due to the stronger social ties between the teachers in the community, the motivating effect of the recommendation panel was stronger. In addition, when the ties are strong, it may be that teachers who would otherwise feel insecure, and as a result prefer to avoid public exposure, would feel that it is safe for them to share their opinion. Concerning the specific issue of avoiding exposure, a possible solution might be to enable writing anonymous reviews, allowing teachers to contribute to the community without worrying about public exposure. More generally, additional work is needed to better understand the plethora of factors that impact teachers' decisions to share opinions with the community.

7.2. The Usefulness Aspect - Teachers' Use of Social Recommendations

Next, we studied teachers' use of the social recommendations given to them in order to find LRs ("the usefulness aspect"). To that end, we conducted temporal analysis of log files of teachers' actions in the system, compared the number of downloads of LRs before and after they were recommended, and triangulated our quantitative findings using qualitative methods - interviewing teachers about their use of social recommendations during their search process. This methodology is different from previous studies concerning teachers' reliance on peer recommendations, which either examined correlations between recommendations and use of LRs, or relied solely on teachers' self-proclaimed attitudes towards these recommendations. We therefore claim that the mixed-methods approach employed in this study provides, for the first time, a strong causal link between recommendations and choice of LRs. The results we obtained from the Physics module revealed substantial use by the teachers of their peers' recommendations, with a statistically significant increase in the number of times an LR was downloaded following it being recommended. The qualitative part of the research validated these findings, with teachers confirming that they did indeed find the recommendations given to them useful.

The interviews with teachers regarding their use of the social recommendations also enabled us to gain additional insights into the factors leading teachers to follow a certain recommendation. The main two factors teaches mentioned in this regard where the relevance of the subject matter to their teaching schedule and the identity of the recommending teacher. The implications of these two factors is further discussed in the 'implications' section below.

Finally, we again note that the results of the 'Usefulness Aspect' in the Chemistry module were extremely different from those of the Physics module. We elaborate on these differences in the next section.

7.3. Strength of Social Ties as Moderator of Social Based Mechanisms' Effectiveness

AS described previously, in both aspects studied – incentive (Study 1) and usefulness (Study 2) – we found major differences between the Physics and the Chemistry communities: results from the A/B testing experiment conducted in the Chemistry module indicated that social recognition had no impact on the Chemistry teachers' willingness to provide feedback. In addition, Chemistry teachers relied to a much lesser extent on social recommendations when searching and choosing LRs. Teachers' responses in the interviews conducted with the chemistry teachers were in alignment with our quantitative findings, with the chemistry teachers attesting that they did not find the recommendations given by their peers useful.

Therefore, in the third part of our research, we wished to better understand the differences in the characteristics of the two teacher communities that might be related to these differences in the results of study 1 and study 2. To that end, we used both qualitative research (in the form of interviews with teachers) and SNA methods. Our first insight from teachers' responses during the interviews, is that the differences in the incentive and usefulness aspects might be interrelated, meaning that the fact that the Chemistry teachers view the recommendations given by peers as less useful to them, also diminishes their motivation to provide such recommendations to other teachers, thus reducing the impact of the RS on their motivation. The interviews also highlighted that both aspects – *incentive* and *usefulness* – are influenced by the strength of the social ties within the community. That led us to the assumption that the Physics teachers' community is characterised by stronger social ties. A social network analysis conducted on the built-in online social networks of both communities, revealed that our assumption was correct – the Physics teachers' network was considerably more inter-connected and contained less isolated users than that of the Chemistry module.

These findings extend our understanding of the advantages of creating and sustaining communities of practice amongst teachers. Some of the benefits that were associated with communities of practice in past works are their ability to create, retain and exchange knowledge throughout an organization (Wenger et al., 1998), to foster feelings of confidence and self-efficacy in their participants (Regalla, Davies, Grissom and Losavio, 2018), to encourage diversity, inclusion and awareness amongst their members (Dutton, 2018), and promote student learning (Moolenaar et al., 2012). Our study adds an additional perspective to those discussed in these earlier works: strong social ties between teachers in a community of practice render social-based mechanisms, such as peer recommendations about LRs and social recognition as an incentive, more effective.

7.4. Limitations

Naturally, there are several limitations to the possibility of generalising the findings from our research. First, the research was conducted in a single learning environment. Other environments catering to other communities of teachers and employing other mechanisms for providing feedback and recommendations, could possibly lead to different insights. However, since this environment serves a nation-wide teacher communities in physics and chemistry, we believe that the results are representative. Second, in this research we focused on the differences in the strength of community ties as a possible explanation for the differences in the behaviour of the two teacher communities. The reason for this was teachers emphasis on the social aspect in their responses during the interviews. However, we do acknowledge that there could be additional underlying factors and characteristics (e.g., culture and context) of the teacher communities that came into play during this research and influenced the results of the study.

8. Conclusions

The conclusions arising from this research are that *social recommendations can indeed assist teachers in their search for suitable learning resources*, and that *social recognition can raise teachers' motivation to provide such recommendations*. However, the validity of these conclusions depends on the characteristics of the community in which the intervention is conducted: the stronger the social ties between the members of the community, the more they will be inclined to rely on social recommendations in their search process, and the stronger the social based incentive mechanism's impact on their motivation will be.

Therefore, designers of learning environments and educational stakeholders who wish to build on these findings and assist their teachers in the task of locating quality learning materials, should devise and implement mechanisms that foster a sense of community between the teachers using the environment. Such mechanisms can include real-life joint work groups and teacher communities, creating discussion forums inside the learning environment, or integrating social network features into the environment (such as those implemented in PeTeL).

Finally, the results of our study serve as yet another reminder of the fact that the process of introducing new technologies into learning environments is never a simple task (Keppell, Suddaby and Hard, 2015), and that different groups of people working in different contexts respond differently to educational interventions (Kizilcec, Reich, Yeomans, Dann, Brunskill, Lopez, Turkay, Williams and Tingley, 2020). In relation to our research, the participatory design process that led to the implementation of the recommendation panel was conducted with Physics teachers only. Therefore, its lack of impact on the Chemistry teachers' willingness to provide feedback suggests that the insights derived when working with the Physics teachers were just not applicable to the Chemistry teachers community. An implication of this to participatory design processes is that we should ensure that co-design phases include users that represent the perspectives and characteristics of the entire target audience.

Regarding future research, we note that the RS that was designed and implemented in this research was a simple 'one-size-fit-all' system, meaning that all teachers were presented with the same recommendations. In future studies it will be interesting to see if personalization of the recommendations according to different teachers' characteristics can improve the incentive and usefulness aspects. Additional directions for future research could also include a more elaborate research into the relations between the strength of community ties and the effectiveness of social-based incentive mechanism, integrating such mechanisms into additional learning environments and teacher communities.

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