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Completed Research Paper

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Abstract

Knowledge sharing in forums is an important part of MOOCs (Massive Open Online Courses). However, the usage of forums to practice knowledge sharing are often inactive and inadequate. To address this problem, we used an action research to build and test a real- time sharing-quality-monitoring mechanism which assesses the quality of answers from text features. The results of this research showed that the mechanism was easy to use and could strengthen one's intentions to share knowledge via regulating its users' knowledge sharing behaviours. However, it may negatively affect peoples' tendency to share knowledge, for example, when they do not want to be monitored and be forced to share or when users feel frustrated using the mechanism. Suggestions for alterations and refinements of the current design are discussed.

Keywords: Human-computer interaction, MOOCs, action research, online education, design science

Introduction

MOOCs (Massive Open Online Courses) are a promising form of knowledge sharing and are considered by many as a disruptive teaching and learning approach which can supply knowledge resources on a massive scale (Aparicio et al. 2014; Ryan and Williams 2014). Defined by Kim (2014), a MOOC is an online course which has the capability to involve a very large number of students, to provide its students with flexible learning pace, and to allow an on-demand certification. Due to these characteristics, most MOOCs (especially cMOOCs, ones featured by their "connectivism" nature and have been launched on mainstream MOOC platforms, such as edX and Coursera) emphasize the importance of social-networked learning and knowledge sharing behaviours among their participants (Beaven et al. 2014; Mackness et al. 2010). Consequently, the traditional way of classroom education, which emphases a teacher-centric way of sharing knowledge, becomes less effective in MOOCs. By definition, knowledge sharing is a human activity via which knowledge is transferred among different people (Gupta, Sharma, & Hsu, 2004). As indicated by Daradoumis et al. (2013) and Mackness et al. (2010), a MOOC's successfulness is largely determined by its effectiveness of knowledge sharing.

However, the current level of peer-wise knowledge sharing on major MOOC platforms is not sufficient (Mackness, Mak, & Williams, 2010). Specifically, as stated by Yousef et al. (2014), it is common to see that MOOC forums having insufficient sharing participation rates and knowledge of inferior level of quality being shared, resulting in high-quality knowledge pieces crowded out by those low-quality ones. Consequently, useful content becomes hard to find, which increases a potential knowledge sharers' frustration and further degrades the participation rate (Graham and Wright 2010). As a result, knowledge starvation becomes common in those forums, decreasing their overall system effectiveness (Onah et al. 2014b; Shtok et al. 2012).

There are varied reasons for these phenomena. Sharing of knowledge can be intrinsically motivated, extrinsically motivated, or both. However, it seems that the effectiveness of those motivations is lowered when people share in a virtual space rather than in a physical space. As Chiu et al. (2006) explained, it is because people tend to feel lower levels of peer pressure for sharing. Fehrenbacher (2017) points out that in a face-to-face environment, constantly adapting a receiver's reaction, a knowledge supplier can adjust and refine his or her content. Rather, in a virtual sharing space, such as a MOOC forum, sharing knowledge is mostly about inputting content into a textbox, where only a very limited amount of feedback about the potential perceived usefulness of the piece of knowledge can be reported back to the sharer. Because the perceived value is often "unobservable" (Sutanto & Jiang, 2013), a positive feedback loop between sharing and motivating cannot be readily established, the sharing process, therefore, may be easily interrupted or stopped.

Many studies exist that focus on the role of using information system solutions to facilitate the IT-mediated sharing of knowledge among people with heterogeneous backgrounds and to provide affordable interaction tools easing the sharing process. For example, Coetzee et al. (2014) implemented a reputation-score-based mechanism to foster knowledge sharing and students' learning outcomes in MOOCs. The results of their study show that their mechanism increases the number of knowledge pieces shared and shortens the waiting time of receiving responses. Howley et al. (2015) tested the effectiveness of using voting (e.g. offering up-/down-voting manipulation) mechanisms and badging (offering stars to good contributors) systems, as well as their interactions. They report that their badge system nullifies the effect of the voting system, and the voting decreases the usefulness of the badges. However, these previous studies tend to focus on creating a sound knowledge sharing ecosystem by filtering for high quality knowledge contributions. Few researches explored how to improve the quality of shared knowledge at the stage of creating knowledge.

To the best of our knowledge, it is still difficult to design and implement a mechanism to regulate knowledge sharing in MOOC forums, and the number of researches on using IS to help do so is limited. There still exist many unknown and context-contingent factors in this realm.

Consequently, three research questions are proposed in this study:

- Is there a viable way to help knowledge sharing behaviours for MOOC platforms?
- How to encourage knowledge sharers to contribute in MOOC platforms?
- How to improve the quality of the knowledge shared by the MOOC platform's participants?

To figure out those MOOC-specific research questions, we conduct action research, a clinical method that can help researchers find a solution for a practical problem and, at the same time, extend the existing theoretical literature (Baskerville and Myers 2004). It is also beneficial in balancing the needs of pursuing scientific research and designing technological artifacts (Baskerville et al. 2018). In our research, grounded on existing kernel theories[1], we performed our rigorous design research through an iterative two-stage process (i.e. a) diagnostic stage; b) therapeutic stage), that simultaneously helps the *praxis* (i.e. mitigation of problems in reality) and the *theoria* (i.e. advances in theory) (Mårtensson and Lee 2004). The theoretical contribution of this study is to apply theoretical concepts including the kernel

[1]According to Gregor and Hevner (2013), kernel theories are descriptive theories, such as natural, social, and human laws and constraints, that inform the designs and the construction of artefacts and solutions.

theories including the technology acceptance model and the theory of time preference. The practical significance is to design a potentially functional and novel pro-knowledge sharing software with a measurably high quality of human-computer interactivity.

The remainder of this article is structured as follows: after an introduction section, a background literature review is presented. The third section will present the method, as well as the findings of the pilot test. The fourth section concludes the article and discusses the limitations of our study and the potential direction for future full research work.

Literature Review

Theoretical Knowledge Sharing Enablers and Inhibitors

Many previous qualitative studies in knowledge sharing and knowledge management have been con-ducted, while summarising several motivational and inhibiting factors. Knowledge sharing, as Barachini (2009) suggests, most often occurs when individuals perceive higher benefits than costs.

Hew and Hara (2007)'s multi-cases study explored seven common factors (collectivism, reciprocity, personal gain, respect, altruism, ease of technology use, knowledge seekers' interest) that can motivate online knowledge sharing. Paulini et al. (2014)'s study further argues that motivational/inhibiting factors are recipient-dependent and time-dependent. For instance, the motivation of short-term participation of knowledge sharing can be extrinsically motivated through, for example, rewards and recognition. Yet, for those members who spent a significant amount of time on these sharing environments, intrinsic motivation such as the feeling of competence and accomplishment is the main driving force for continuous participation. Also, a person's primary motivation type changes. For example, although many people chose to share for obtaining extrinsic rewards and recognition, this expectation fades away over time. Nonetheless, some types of motivating factors, such as the seeking for challenges, developed some time during the participation. Rai and Chunrao (2016) state that most learners of MOOCs choose to participate in these courses largely due to intrinsic factors (e.g. being genuinely interested in finishing a course and deriving fun in solving challenging assignments).

Rewards and recognitions, as extrinsic factors, may simultaneously "crowd out" (Bartol and Srivastava 2002) and "crowd in" the intrinsic motivations to share knowledge (Bartol and Srivastava 2002; Dyer and Nobeoka 2000; Frey and Jegen 2001; Frey and Oberholzer-Gee 1997). Based on empirical studies, some researchers also found that anticipated extrinsic rewards created a negative effect on people's attitude towards sharing knowledge and, consequently, reduced their intention to share it (Bock and Kim 2001; Bock et al. 2005). Therefore, we need a design that can maximize the motivational factors of extrinsic rewards without crowding out intrinsic motivations.

Therefore, there is a need to understand how to maximise the motivational effects of rewards and recognitions. One of the potential theoretical directions is the Expectancy-value theory, which argues that the effect of rewards is time-dependent. People tend to prefer immediate rewards to delayed ones (Frederick et al. 2002; Silverman 2004). In terms of rewarding, the effectiveness of "smaller but sooner" rewards is generally larger than "larger but later" ones (Li et al. 2010). Immediacy of rewards is vital for people in developing motivations, and, as Ryan et al. (2006) explained, it is this immediacy that provides prox-imal psychological determinants motivating people to engage in activities such as games-playing. This immediacy factor may be applicable to the development of educational tools (Richter et al. 2015), and it also implies that, when designing the system, it is essential to give the motivating mechanisms an explicit position and the effect of it as immediate as possible.

Information System Designs to Increase Knowledge Sharing Propensity

In practice, information system developers attempt to integrate the above-mentioned enablers and barriers into information system designs, and one of the design principles for designing is to maximize the benefits of the enablers while minimizing the effect of the inhibitors (Barachini 2009; Cheng and Vassileva 2006). For instance, Saad and Haron (2014)'s case study suggests that it is viable to design and to implement an sufficient and timely acknowledgment system to stimulate knowledge sharing among scholars without giving a prototype for evaluation. Also, the generalisability of this system model might also be a problem, because the case used in this study, a single large-scale Malaysian public university, has only limited representativeness.

Vassileva (2002) and Cheng and Vassileva (2005)'s studies found that merely implementing rewards to motivate sharing behaviours in an online community may cause some users to try to game the system, resulting in a massive production of resources of medium or low quality, which made it difficult for users to locate high-quality resources. Also, these excessive low-quality resources may result in an "information overloading" problem, causing users' satisfaction loss and people leaving the platform (Jones and Rafaeli 1999). Therefore, the evaluation, the incentivization, and the controlling of the quality and the overall quantity of user contributions are essential (Vassileva 2012).

In terms of inhibitor minimization, Schwen and Hara (2003) argue that fostering a community of practices (CoP) can mitigate the level of negative effects of several knowledge-sharing problems, such as the lack of physical interactions. However, the authors do not mention any practical solutions to solve this problem. In terms of the final outcomes of this project, the authors merely mentioned "mixed results were found", but the authors do not explain in detail the unintended failures. Sutanto and Jiang (2013) found that a "semantic score" had a positive effect on people's knowledge sharing frequency and tendency. Similarly, Jabr et al. (2013) studied various user support forums (i.e., Apple, Oracle, SUN, and SAP) and hence concluded that forums with explicit feedback-based recognition mechanisms can have an increased level of users' contribution behaviours, as the pro-sharing culture of the forums might be fostered and that these forums' overall quality and efficiency were improved. Generally, in an online environment, there is a lag between the time one shares knowledge and the time others recognize it, which often takes weeks, and this lacking synchronicity inevitably attenuates the effect that a motivational factor has on stimulating knowledge sharing (Ma and Agarwal 2007). We, therefore, assume immediacy should play an important role in our proposed design.

Specialties of Sharing Knowledge in MOOCs

The reason why sharing knowledge in MOOCs is so special, according to Mackness et al. (2010), is that an ideal MOOC is expected to meet four standards:

- Autonomy (i.e. students of MOOC have high flexibility and control over their learning and other engagements);
- Diversity (i.e. learners are from very diversified backgrounds, have different levels of expertise and prior knowledge);
- Openness (i.e. the course itself ensures the free-flow of information through the network and thus stimulate a culture of knowledge sharing and creation); and
- Connectedness (i.e. the technologies linking everyone together and making all the other three characteristics possible)

Nonetheless, Mackness et al. (2010)'s paper argues that these standards, to some extent, inhibit the sharing of knowledge. For instance, diversity in ages, in cultures, and in prior knowledge levels poses an extra burden on interpersonal communications and lowers a potential sharer's knowledge sharing intention. Furthermore, due to the large enrolment numbers and the highly diversified participants, traditional ways of teaching support with a teacher-centered learning moderations style, are no longer applicable in MOOCs, whilst it is the interactions among the peers that are endorsed. However, the active participation rate of such interactive sessions is low (around 14%).

Discussion forums, the interactive places where students, tutors, and teachers can share ideas, ask questions, offer peer-wise help, and make up social interactions with each other, are the main arenas for knowledge sharing behaviours on MOOCs platforms (Yang et al. 2014). However, according to Kizilcec et al. (2014), most of the forums are largely underutilized, and only a small fraction of the learners report they are benefiting from participating in those forums, and according to Onah et al. (2014a), the proportion of active forum participants is rather low (around 15%). Wong et al. (2015) test the effectiveness of using reputation systems to regulate users' forum participation but found only limited usefulness. As implied by Boroujeni et al. (2017), it is hard to build a sustainable knowledge-sharing community as the fluctuation in users' forum participation (active users' activities, threads patterns) is quite large.

Information System Action Research

Stringer (2013) defines action research as a participatory approach that typically collaborates with communities (who are as well the focus and eventual beneficiary of the research) and seeks to find a local solution for problems under certain circumstances. A good action research both satisfies the need for scientific rigor and the promotion of a sustainable social change. As implied by Baskerville and Myers (2004), action research provides a valid way to improve the practicality of information system studies in the human context.

According to Baskerville and Myers (2004), action research has many variations and forms. Susman and Evered (1978)'s canonical action research methodology states that the process of action research shall be both cyclical and iterative. Each research may contain several cycles and iterations, and, in each iteration, researchers need to go through five phases, including problem diagnosing, action planning, action taking, evaluating, and specifying learning. Applying Lawler (1994)'s competency-cantered theory, the researchers argue that, for a knowledge-intensive company, it is essential to replace its legacy system which adopts a job-based paradigm by a system that embodies the skill-based paradigm. The evaluation strategies include one experiment and four workshops, where the experiment was used to give the end-users a hands-on experience and the workshops aimed to collect feedback and reactions to the prototypes. For another, Mårtensson and Lee (2004) adopt a dialogical action research design to identify current information system flaws and to initiate possible mitigations. This method, as they argued, predominantly relied on interviews, whilst other types of methods, such as observations and documentation and archival records analysis, are complementary. Therefore, in their research, they mainly conducted two types of interviews: semi-structured interviews and unstructured ones. In the semi- structured interviews, they worked with the practitioners to identify and understand the inefficiencies in their daily operations. In the end, the authors argue that the successfulness of a dialogical action research is determined by the ability to facilitate reflective dialogue which gives the practitioners and the researchers an opportunity to enhance mutual understanding, to identify current business problems, and to develop research-based interventions. Via reviewing historical context and origins of action research and practices and synthesizing previous action research types Hayes (2011) and Council (2005) offer a state of the art handbook that offers a guide for researchers who want to perform such research. Our research referenced the structures and processes introduced in their articles.

Method

Our study applied the Council (2005)'s Double Diamond model, one of the most recent and appropriate models for designing in system innovation. Compared to other popular designs models, such as the Hasso-Plattner Institute's, IDEO's Human-centred Design Model, and Design Thinking 3 I's (Inspiration, Ideation, Implementation) model, the Double Diamond model is more complete, detailed, business and management-oriented (Tschimmel 2012). The study contained four cycles (see Figure 1), i.e., Discover, Define, Develop, and Deliver, and at the end of each cycle, a reflection and evaluation session will be executed to determine if there is a need to roll-back to the last stage or to proceed to the planning of the next stage.

Stage 1: (Discover) Content Analysis

The first stage aims to find common knowledge sharing problems and their possible root causes. For this, we conducted a content analysis of the posts published on an existing MOOCs' discussion forum.

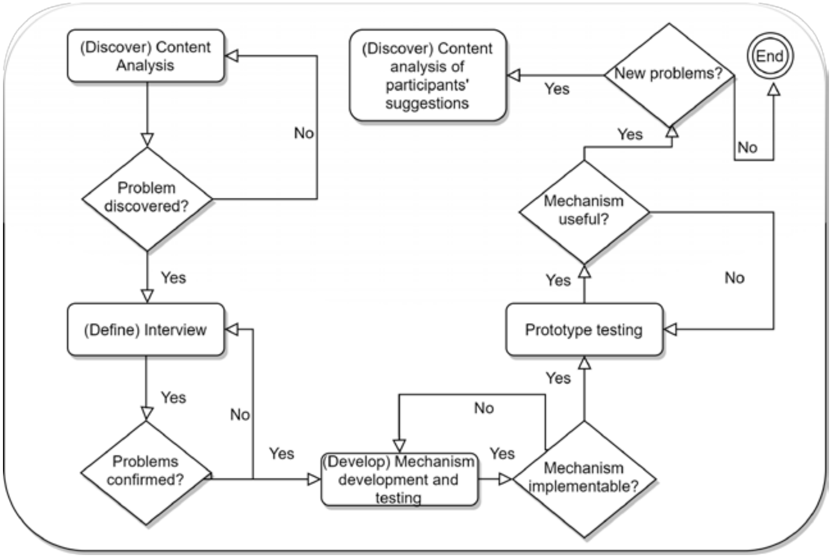

Figure 1 Action Research Spiral -- An Iterative Cycle of Planning, Action, and Reflection

Following Bhattacherjee (2012)'s guidance, the content analysis stage comprises of three phases: The first phase included the sampling of courses. One of the largest MOOC platforms, edX.org, was selected as the subject of our research, and on that platform, 10 courses were randomly chosen for auditing (enrolling without paying a fee) to access the texts in their course forum. The random selection process was based on a full list of the currently available courses obtained by a specialized crawler developed by Shi et al. (2018). The second phase was a unitisation of posts. Posts that entail the existence of knowledge sharing problems were selected for analysis and the texts in the posts were divided into segments that are treated as "separate units of analysis". In the third phase, after analysing those unitized text chunks, we categorized the problems and assigned a name to each category. Potential problems and their examples were summarised in Table 1.

Table 1 A List of Categories of Knowledge Sharing Problems and Barriers and Their Example

Name of potential problems	Example
No functional forum for knowledge sharing at all	As of 9/4/2018, the course <Introduction to OpenStack>, opened in 2016, has no post in its forum.
Good-quality posts are "submerged" by low-usability posts	In the course <Introduction to Management Information Systems (MIS): A Survival Guide>, useful posts are effectively hidden by posts of low-usefulness, such as greetings and expression of thanks.
Posts with an ambiguous or meaningless title	In the course <CitiesX: The Past, Present, and Future of Urban Life>, a post triggers a meaningful discussion, but the title of that post is "NA". If the title were more meaningful, it would raise more knowledge sharing intentions.
Posts are written improperly or use informal style of writing	A post in <Astrophysics: The Violent Universe> says "^.^ Interesting...but it is about telescopes and that".
Posts that only give an expression of emotions	A post says "ONDE!!!! EXCELLENT..!!!!!! Praise to professors".
Posts that only contain knowledge unrelated to the current discussion topic	A greeting, which should be posted in a dedicated welcoming thread, instead posted under an academic topic.

Stage 2: (Define) Online Interview

We then conducted online interviews with volunteer participants. The average duration of the interviews was 23.2 minutes. We used a linear snowballing method to diversify the participants' demographic backgrounds: we summoned our initial participants in an Australian university during semester break time and asked them to refer to a friend or workmate who has a slightly different background. We excluded people from our experiment if they did not have MOOC experiences at the time of our study. The collection stopped when we found there were no new insights given by the participants, and in the end, we obtained a sample size of 46. Table A1 describes the participants (in the Appendix).

The interview unfolded as follows: The first part of the interview was an icebreaker session asking participants' MOOC-related learning and sharing experiences (e.g. frequency, time, efforts level, and outcomes, etc.). Questions in the second part checked the validity of the potential problem list. In the third part, the researcher worked with the participants to analyse and find potential causes and possible solutions.

Except one participant stating "I won't read them anyway" and another stating "MOOC forum is a place where people can discuss freely" and "informalness [*sic*] essentially is not a bad thing", all other participants agreed with the knowledge sharing problems identified in our previous stage. As one participant noted, he only uses discussion forums to "ask instructor [*sic*] about assignment things, hoping the problems (questions) are shared by my fellows". He also reported "when it comes to knowledge sharing with peers, one of the problems of those forums is the posts in there are sometimes in [*sic*] very low quality. No one even reads them." Another respondent noted the problem of low participation rate of those forums and argued the cause of those problems is the long waiting time: "the lecturer didn't pay much attention to the online discussion. It usually may take more than 3 days to get [*sic*] reply". One respondent argued "for some non-popular courses there is even no comment or post at all.", and this argument corresponded to another respondent's comment, stating "the essential problem is to improve the usage of the forum". To solve these problems, a respondent suggested the forums should be "disciplined and managed timely", though she also said to manage, in real-time, a MOOC forum can be very difficult. Another suggested using tools that ensure effective interaction. Three respondents also suggested to provide more guidance to forum users, and the best timing of giving guidance, as one respondent argued, is real-time.

Stage 3: (Develop) Mechanism Developing and Testing

As Cohn (2004) suggests, functions provided by software should be determined by its user's demands, expectations, and requirements. To achieve an effective system which allows real-time monitoring with minimal costs and prompt incentivization, we deem that a functional "machine" should be able to calculate the quality of those text-based posts in real-time and to immediately report this value to the knowledge editor, and, consequently, to encourage acceptable knowledge sharing behaviours and to punish undesired one simultaneously.

We designed a simple prototypical solution that was in the form of a JavaScript-based plugin. It evaluates the quality of a knowledge input by monitoring a set of textual features, including length, readability, and style. The plugin used a Natural Language Processing (NLP) library developed by Kelly (2016) named *NLP_Compromise*.

The system's objective is to motivate people to share more high-quality knowledge and discourage people to share bad ones. Also, it can automatically determine whether a piece of textual input is merely a junk text. In such cases, it warns the writer not to make such inappropriate input. Moreover, a rule-based mechanism was implemented to monitor and to identify a pre-defined list of problems such as posts without proper netiquette, a set of rules to encourage tolerant, polite and considerate online behaviours amongst Internet users (Sturges 2002).

As Figure 2 shows, we designed three models of ratings in this prototypical work: i.e. a photographic one (Model A), a numeric one (Model B), and a textual one (Model C). Model A estimates a knowledge piece's quality and used a pointer to report it back to the writer. Model B, instead, reports an estimated score to the pointer. Model C tries to catch users' improper behaviours and gave corresponding guidance (e.g. "please do not use too many emotional words" and "your post needs further construction") to the users. All three models monitored only the main body area. We predicted that our mechanism might cause a spill-over effect on title-editing, meaning that when people refine their main body based on the mechanism's feedback, they may also want to refine the title, so participants can perceive the effect of the mechanism not only when they edit the main body but also when they edit the title.

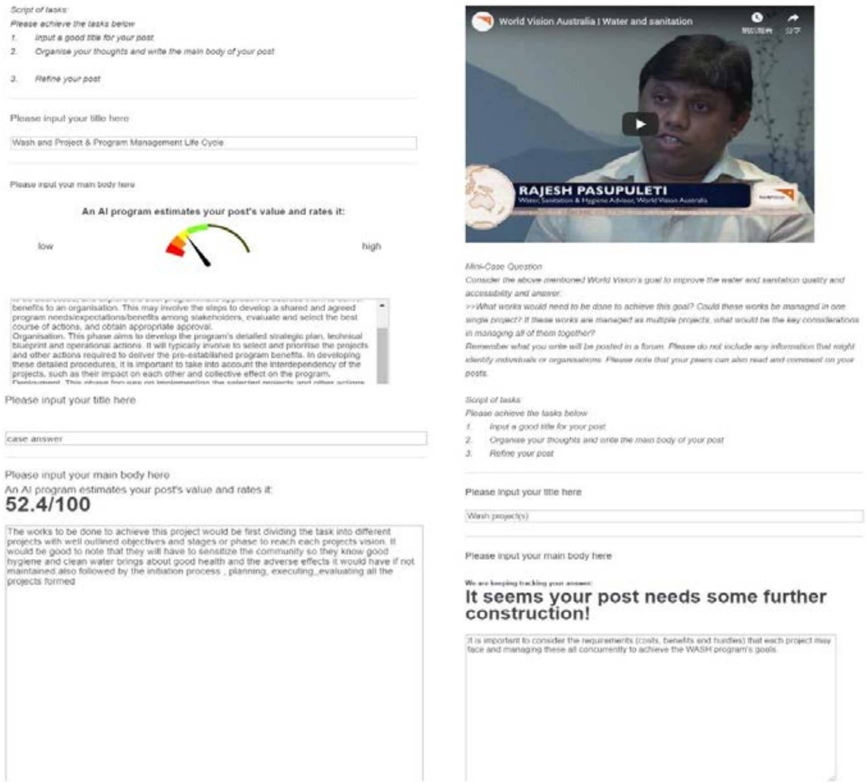

Figure 2 Model A, Upper Left; Model B, Bottom Left; Model C, Central Right

Stage 4: (Deliver) Prototype Testing

We tested the prototype in an online environment, and the participants were asked to access the prototype via a link using their preferred device (i.e. the device they commonly used to login to a MOOC). We describe the participants in Table A1 (Appendix). To gather evidence that would support a system design that better facilitates knowledge sharing, we also summoned a control group to provide a base of comparison. We followed a random assignment approach to assign participants into different treatment/control groups, and the participants did not know the existence of their peers.

We asked the participants to discuss a mini case question in a MOOC for Project Management. The question was designed to let the students distinguish the difference between project management and program management, a process of managing several related projects. Both the treatment and the control groups received the same questions in the same environment. Each participant in the treatment group accessed one model. People who accessed Model A and B saw the questions along with the "displayer" that showed the sentence: "An AI program estimates your answer's value and rates it: *x*", where *x* reflected the algorithm's assessment of each participant's contribution. For Model A, high-quality inputs caused the indicator to move from the left (the red area) to the right (the green area). For Model B, high-quality inputs caused high-quality score. People who accessed Model C were given advice on what they were writing. After that, they rated the prototype on a 5-point Likert scale (5 = definitely yes, 4 = probably yes, 3 = might or might not, 2 = probably not, 1 = definitely not) to test the subjective effects of the prototypical mechanism. Eight such questions are listed in Table 2. The questions were adapted from Venkatesh and Davis (2000)'s Technology Acceptance Model (TAM2) model.

Table 2 Prototype Testing Result for Model A, B, C and Control

	Treatment			Control
	Model A	**Model B**	**Model C**	
Cases	10	13	8	10
Length of contribution (in characters)	M = 906.6 SD = 501.77	M = 1158.0 SD = 494.78	M = 708.1 SD = 466.52	M = 275.1 SD = 122.00
Duration of participation (in seconds)	M = 2023.3 SD = 721.2	M =2250.0 SD = 1316.07	M = 1774.9 SD = 1497.3	M =1144.1 SD = 841.5
Perceived usefulness in improving performance when making contributions	M = 4.12 SD = 0.35	M = 3.93 SD = 0.92	M = 3.38 SD = 1.30	Not Applicable
Perceived usefulness in improving productivity when making contributions	M = 4.00 SD = 0.53	M = 3.71 SD = 0.99	M = 3.00 SD = 1.07	
Perceived engagement to write good quality contributions	M = 3.63 SD = 0.74	M = 3.93 SD = 1.14	M = 3.38 SD = 0.74	
Learning to interact with the mechanism is easy	M = 3.75 SD = 0.46	M = 3.79 SD = 0.97	M = 3.25 SD = 0.71	
Becoming skilful at using the mechanism is easy	M = 3.50 SD = 1.07	M = 4.21 SD = 0.89	M = 2.75 SD = 1.28	
Be encouraged to have better quality contribution when editing the title	M = 2.63 SD = 1.19	M = 2.93 SD = 1.27	M = 2.88 SD = 0.83	
Be encouraged to have better quality contribution when editing the main body	M = 3.88 SD = 0.64	M = 3.43 SD = 1.34	M = 2.75 SD = 0.71	
Be encouraged to spend more time on refining the knowledge contribution	M = 4.25 SD = 0.71	M = 3.50 SD = 0.85	M = 2.88 SD = 1.36	

Our result (see Table 2) shows that our participants spent longer time on editing answers when Model A and B was presented, compared to the participants in the Model C group. Participants in the treatment group also provided longer answers on average than people in the control group. Among the three models, Model A outperformed others in terms of its perceived usefulness in improving the performance and productivity of writing knowledge contributions. Model B was perceived to be easier to interact with. All of the models obtained a low score in the title-editing question, indicating that our anticipated spill-over effect might not happen: although our participants agreed the mechanism might encourage them to make better quality contribution when editing the main body part, it probably would not encourage them to do so for the title part. Model C received lower ratings in all measures. Particularly, we found the participants deemed Model C would probably not encourage them to spend more time on editing nor refining knowledge contributions. That said, Model C's large SD values implied the users had conflicting judgments on it.

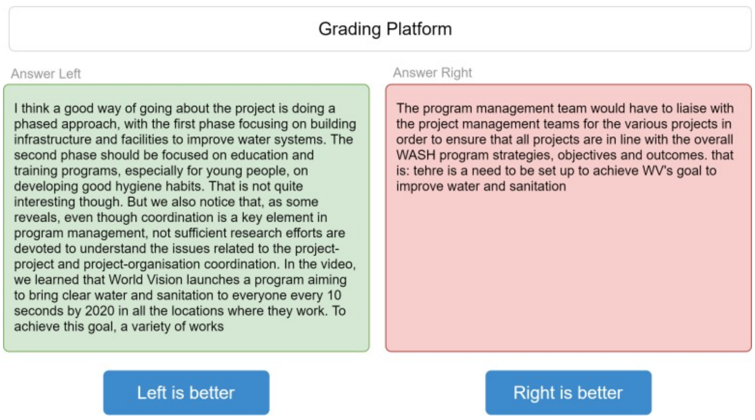

Figure 3 An illustration of the grading platform

To further validate the quality of the knowledge contributions, we asked three online course tutors to judge the quality of the answers that the participants provided. To do so, they used a website that we built (See Figure 3). We set up different (password-protected) accounts for different graders so that each one could not see or change another grader's decisions, and graders could not interact with one another when grading. The graders assessed two responses to the same question at a time, and they needed to judge which one had better quality based on their teaching experience, and the better one will get one "point". Each answer will appear four times and each answer had an equal chance to appear before the graders accessing it. The range of points will be zero to four.

Table 3 Multiple Comparisons of the knowledge contribution quality scores for Model A, B, C, and Control, using a Tukey post hoc test

Group		Score Mean Difference	SE	Sig.	95% CI (L, U)	
Model A	Model B	-0.395	0.397	0.753	-1.463	0.673
	Model C	0.942	0.448	0.171	-0.262	2.146
	Control	1.400*	0.422	0.011	0.265	2.535
Model B	Model A	0.395	0.397	0.753	-0.673	1.463
	Model C	1.330*	0.424	0.016	0.196	2.477
	Control	1.790*	0.397	0.000	0.727	2.863
Model C	Model A	-0.942	0.448	0.171	-2.146	0.262
	Model B	-1.336*	0.424	0.016	-2.477	-0.196
	Control	0.458	0.448	0.737	-0.746	1.662

*. The mean difference is significant at the 0.05 level.

We used a one-way analysis of variance (ANOVA) to determine whether our proposed mechanism can cause a significant increase in the participants' quality scores. We first checked the assumptions required for the analysis and found no major problems. Results showed that our mechanism proved effective on improving contributions' quality ($F(3,37) = 8.295$, $p < 0.001$). Specifically, as Table 3 indicates, the average scores received by the participants in Model B was the highest among the four groups. That said, there was no statistically significant difference between Model A and Model B. Although the Model C's participants received a higher average score than the participants in the Control group, the difference was not significant either.

We obtained a substantial level of agreement among the graders (Intra-class Correlation Coefficient, ICC (3, 3) was 0.832 with a 95% confidence interval from 0.717 to 0.905, $p<0.001$), indicating the proposed mechanism provided strongly reliable scores.

We asked the respondents to write comments on the solution about the improvements or disadvantages, if any, brought by the prototypical solution. We read comments together with the participants to determine whether they have further suggestions and whether there exist misunderstandings. Based on the comments, we found the participants primarily appreciated the straightforwardness and easiness of the mechanisms in Model A and B. Several participants mentioned that the mechanism (the AI) was "sufficiently smart". As one respondent put, it (the mechanism) remind [*sic*] to write a quality answer at all times. So when I was typing, I feel more pressure or responsibility to write a good answer. Two participants reported the mechanism "mitigates the boringness of writing answers" and "gamifies the process of sharing", and it would "especially suitable for people who always want to win and get a better ranking or score".

The participants also pointed out several potential problems. One respondent mentioned his or her concern is about the computational burdens, as he or she found his computer became slow after he or she inputs a lot of words. A similar concern was raised by another participant who accessed Model A, reporting a bug that "the indicator stopped running when my paragraph went long". After we traced and reproduced this bug, we concurred the idea of the computational burden as we found the waiting time became significantly longer when a contribution was over 1,500 words.

Another respondent commented, *"the machine gives me an impression that it push [sic] me to share my knowledge or then make me feel that I am forced to do this, which makes me feel really unhappy and* *uncomfortable."* Respondents also gave suggestions for improvements. For instance, a respondent argued that a "turn-off" button should be added to satisfy the demands of the users who disapprove of such a sharing-motivator. A computer-science background participant suggested using mobile web content adaptation techniques so that the software can be perfectly run on devices with screens of different sizes.

Conclusion and Discussion

In conclusion, in this study, based on kernel theories, we utilized an action research approach to design a viable prototype for motivating learners' sharing behaviours such that they will contribute more high-quality knowledge on MOOC platforms when the intervention of our proposed mechanism presents. This study also aims to extend the existing knowledge sharing literature by applying several existing theoretical concepts and models, such as the utilization of the theoretical knowledge sharing enablers and inhibitors, people's time preference for rewards, and users' subjective acceptance towards the mechanism.

The prototypical design is a success in terms of its perceived usefulness and perceived ease of use reported by the participants. Our participants spent a significantly longer time on writing longer and better knowledge contributions once our mechanism presents. Additionally, we observed that some participants preferred to refine their knowledge contribution after finishing their first draft. We postulate that people in the control group with this preference of refining answers might have taken more time on refining their answer as they have less idea about answer quality as they had no feedback mechanism. By contrast, people in the treatment group might have taken less time on refining because they were interacting with our mechanism which gave explicit feedback messages informing them what might make an answer potentially better. The participants in the treatment group, therefore, saved some time on refinement. Our participants agreed that the mechanism gives them, in real-time, feedback about their posts' estimated quality and, therefore, motivates them to provide better contributions and discourages them to give inferior ones. In terms of the reported performance issues, a variety of commercialized textual-feature-based English word processors, such as Grammarly, Read & Write and Gold Write Away, have been developed (Lew et al. 2018), which indicates that a real-time processor is viable and profitable. We therefore argue that our proposed mechanism could be implemented efficiently because there is proof from those tools.

This research has some limitations. First, due to the limitation of time and money, this study only audited ten courses for the unitisation of problems in MOOC forums. Also, currently it contains a limited number of respondents, and the selection of respondents is not randomized, which may entail biases. In addition, all of the respondents are from the same country (i.e. Australia) which weakened the representativeness. Third, as mentioned in the literature review section, people's attitudes towards motivational factors change over time, but at this stage, there is no data collected to monitor within-sample intertemporal changes. Fourth, the testing environment of this study is in a simulated project management course, but field works on a cross-courses environment are recommended. To mitigate those problems, we will identify more MOOC-specific knowledge sharing problems from more courses, from a larger student sample, by repeating the design approach in several different courses and evaluating accordingly.

It is expected that the outcomes of this study eventually can lead to the invention of a real-time Artificial-Intelligence-based knowledge evaluation tool with high accuracy, semantic-aware capability, and comprehensive pre-defined problem lists. It shall also consume little computational power on the client-side and be accessible on different devices. By utilizing machine learning techniques (e.g. Latent Dirichlet Allocation), such a mechanism shall also be able to check a post's topic relevancy. However, to the best of our knowledge, so far only "supervised learning algorithms" are viable to calculate factors such as topic-relatedness, which implies the necessity of forcing the practitioners to prepare data (e.g. large corpora of textual documents) to train the machine even before the launch of the course. In terms of this problem, we speculate that it may be helpful to make predictions based on documents extracted from a similar, recently offered course. Nonetheless, this is not a perfect solution to the problem and implies that more design science research is needed in this area.

Appendix

Table A1 Demographics of Participants, Age, Working Status, MOOC Experiences, and Education Level

Factor	Group	Stage 2: (Define) Online Interview				Stage 4: (Deliver) Prototype Testing			
		Male (n=26)		Female (n = 20)		Male (n=27)		Female (n = 14)	
		N	Percent	N	Percent	N	Percent	N	Percent
Age	<21	2	7.69%	4	20.00%	2	7%	2	14.29%
	21-25	7	26.92%	6	30.00%	10	37%	4	28.57%
	26-30	14	53.85%	8	40.00%	14	52%	7	50.00%
	>30	3	11.54%	2	10.00%	1	4%	1	7.14%
Working status	Employed	14	53.85%	6	30.00%	7	26%	2	14.29%
	Not working/ Studying	8	30.77%	9	45.00%	19	70%	7	50.00%
	Prefer not to answer or did not respond	4	15.38%	5	25.00%	1	4%	6	42.86%
How many MOOCs taken	1-3	15	57.69%	11	55.00%	8	30%	11	78.57%
	4-6	5	19.23%	5	25.00%	12	44%	1	7.14%
	6 or higher	6	23.08%	4	20.00%	7	26%	2	14.29%
Highest level of education completed	College/Bachelor’s degree or lower	11	42.31%	9	45.00%	9	33%	3	21.43%
	Master’s degree	12	46.15%	6	30.00%	15	56%	7	50.00%
	Doctoral Degree	1	3.85%	1	5.00%	2	7%	0	0.00%
	Prefer not to answer or did not respond	2	7.69%	4	20.00%	1	4%	4	28.57%

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