Wish Wall: Helping Each Other in College

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ABSTRACT

In modern society, college students are facing great pressures from different aspects of life. This huge pressure is largely rooted in the accumulation of small problems in life. If those small problems could be solved in a timely manner, the pressures on them will gradually weaken and even disappear. Psychological studies have proved that expressing wishes and being aware of support existence are highly effective and healthy ways to reduce people's fear associated with real-life challenges and find strength to tackle the problems. To this end, we build a wish wall (an online wishing and helping) mobile platform, where students can make use of text and pictures freely to put forward their wishes in the categories of study, family, peer relation, romantic relation, self-cognition, career planning, and so on. After that, the backend will recommend other capable potential support users to help the wish raisers to accomplish the wishes. In this way, we are able to make the users contact online while solving their wishes offline, and finally achieve the goal of helping each other. Our user study with 17 senior college students showed that upon 10 raised wishes (3 on study, 1 on internship, 3 on career plan, 1 on parent relation, and 2 others), half of them were responded with satisfaction, demonstrating the effectiveness of the wish wall platform.

CCS CONCEPTS

• **Information systems → Social networks**; *Collaborative filtering*; • **Social and professional topics → Adolescents**;

KEYWORDS

Wish Wall, pressure, college student, wish raiser, wish supporter, recommendation

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1 INTRODUCTION

With the rapid development of economy and society, the psychological pressure of college students is becoming bigger and bigger. They face the pressure from academic life, emotional problems, career planning, and so on. However, contrary to the big problems they are facing, their abilities for personal emotion control and adjustment are still relatively deficient, which will cause extremely serious consequences. These enormous pressures often come from the accumulation of small problems in their real life, and if students can be given timely help when they are in trouble, they can greatly reduce the stress they are suffering. What's more, this will have significant implications for students' future lives [2–4].

Psychological studies have proved that expressing wishes and being aware of supports are highly effective and healthy ways to reduce individual's fear associated with the encountered problems [6]. For students who are still at the sensitive growing age, these can particularly enable them to build up confidence and strengths in moments of social connection [7].

The aim of this study is to deliver a wish wall mobile platform, aiming to provide college students with an online wishing and helping platform. On this platform, students are able to publish their problems with text, pictures and timestamp information, and the system will automatically recommend the problems to the candidates by whom those problems could be solved based on the backstage recommendation algorithm. If the candidate accepts the problem, s/he will obtain the contact way of the student who put forward the problem. In this way, the candidate is able to contact that student and help him solve the problem. Finally, we can achieve our goal of helping each other.

There are several related mobile apps in the industry, such as My Wish List [8] and Throwmemo [14], which allow users to submit their wishes on the app and provide rich color for sorting and listing. However, they do not provide users with practical solutions to the wishes. On the contrary, the wish wall platform in this paper not only allows users to express their own wishes, but also encourages other users to help accomplish the wishes. What's more, during this process, student users could know more friends, enabling them to expand the circle of communication. This is the main difference from the existing solutions in the literature.

We conducted a user study among 17 senior students at Tsinghua University, who raised 10 wishes (3 on study, 1 on internship, 3 on career plan, 1 on parent relation, and 2 others). Half of the wishes were responded with satisfaction, demonstrating the effectiveness of the wish wall platform.

The remainder of the paper is organized as follows. We review some closely related work in Section 2. The framework of the wish wall mobile web platform is illustrated in Section 3, followed by its performance evaluation in Section 4. We conclude the paper and outline the future work in Section 5.

2 RELATED WORK

The study is closely related to the following two areas of work.

2.1 Recommendation Systems and Techniques

Recommendation systems. With the rapid development of Internet, especially mobile Internet, the amount of information produced in the world is increasing exponentially, which satisfies the demand of various kinds of information in the new era greatly. However, at the same time, users have to face a lot of information they are not interested in, resulting in the so-called "information overload" phenomenon. The effective way to solve this phenomenon is to use the recommendation systems [1, 12, 13]. It can recommend goods that users may be interested in to them, according to their personal preferences and needs and other information, combined with the product description. In essence, a recommendation system is an information filtering system that predicts a user's "scoring" or "preference" for a product that has not been used or evaluated. Due to the rapid development of the electrical and commercial industry, the recommendation systems have become quite popular in recent years, and have been used in all walks of life [5, 9, 11].

Application of recommendation algorithms in this study. In the system built in our article, whenever the user presents a new problem, the system needs to recommend the problem to the appropriate problem solver based on the backstage recommendation algorithm, in order to save the user's lookup time and improve the probability of successful solving. The industry has a great demand for the research and application of recommendation algorithms, so there are a variety of recommendation algorithms applied to different specific scenarios, of which the most popular one is content-based recommendation algorithm and collaborative filtering recommendation algorithm. In reality, most of the major Internet companies adopt the hybrid recommendation algorithm, i.e., the fusion of various recommendation algorithms, to achieve the better stability of the system. Therefore, this paper adopts the hybrid recommendation algorithm, which integrates the two ideas of content-based and collaborative filtering, comprehensively utilizes the information of the problem itself, the personal information of the problem provider and the user's usage information.

2.2 Natural Language Processing

Natural language processing. Natural language Processing (NLP) is designed to allow machines to understand and process languages in a specific way by using a variety of data processing techniques. Since the vast majority of data generated on the Internet is still text, how to effectively understand and apply this information is a concern of many internet giants, so that the field of research is very popular. Because of the application requirement in our system, this paper focuses on the technique of text similarity calculation.

The application of NLP technology in this paper. Among the recommendation algorithms mentioned above, one of the key steps is to compute the similarity between the new problem and the problem that the user has solved, in which the text similarity computing technology plays a vital role. Through this technology, we can get the similarity between two problems.

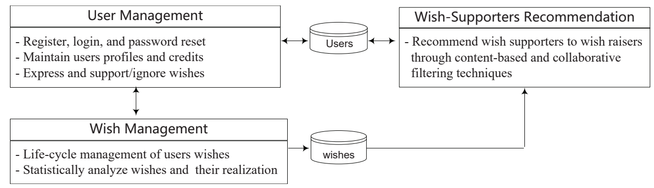


Figure 1: The Wish Wall framework

3 THE FRAMEWORK

The wish wall platform is based on web app technology, which can be exported to iOS and Android two versions. Figure 1 shows the framework of *WishWall*, which is comprised of three major modules, namely, *user management, wish management*, and *wish-supporters recommendation*. They cooperate as follows.

3.1 User Management

The module has three responsibilities.

First, it manages users accounts. Users register the Wish Wall application through their college e-mails (Fig. 2(a)). During registration, they also need to fill out such personal information as major, grade, gender, and contact phone number (Fig. 2(b)). Since only the students from the same college can register as users, users wish-support potentials could be guaranteed. More importantly, the risk of privacy leakage will be constrained to a small scope. Users can edit their personal details and check the number of wishes that users have supported through their profile pages.

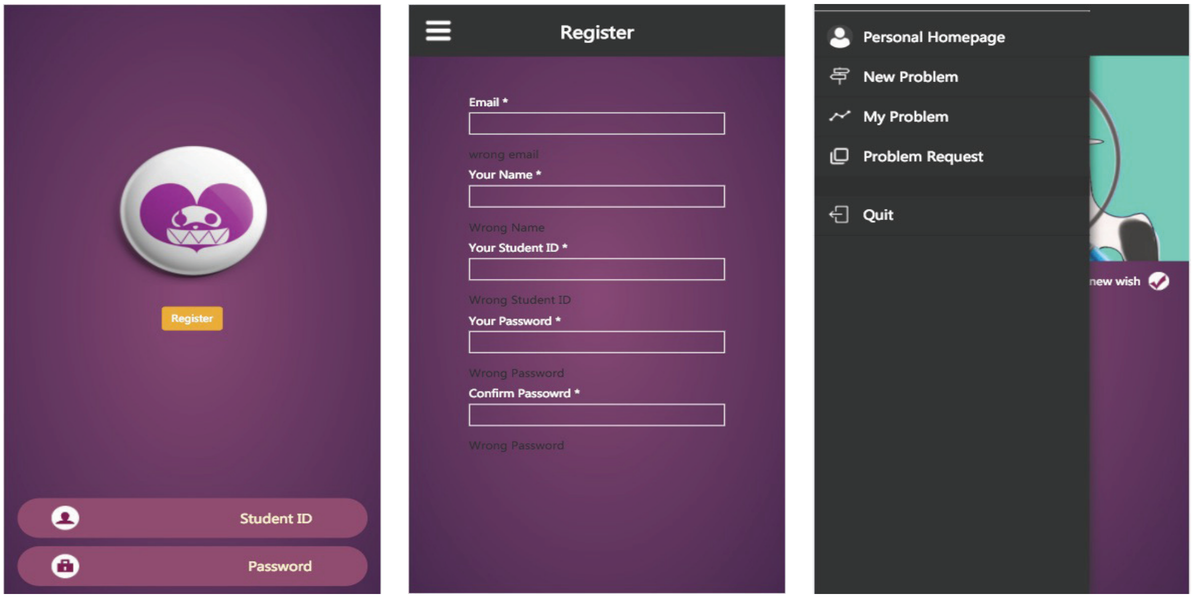
Second, users on the Wish Wall platform help each other, and can play two types of roles, i.e., **wish raiser** and/or **wish supporter** with the guidance entrance (Fig. 2(c)).

Wish raiser users are free to publish their wishes on the platform by filling in the title, type, temporal deadline, and description of the wish. Up to 9 pictures can be added to augment the description of the wish. The Wish Wall platform supports over 20 types of wishes in the six major categories (*study, family, peer relation, romantic relation, self-cognition*, and *career planning*) that youths are typically confronted with.

Figure 3(a) illustrates a user's new wish, which is to solve a question about probability theory in a textbook for his assignment. The attached picture shows the book page which the question comes from. The platform will recommend it to N potential wish supporter users, where N is set to 5 in the study. The more wishes a user helped, the higher priority he has, and thus more wish requests he will get.

Figure 3(b) is a list of wishes that the user raised. Clicking on any wish in the list, a complete wish description will be displayed, as shown in Figure 3(c).

Third, wish supporter users can view all the wish requests that the platform recommends to them.They can decide to accept or ignore the requests, subject to their own abilities and willingness. To protect wish-makers privacy, only after a user accepts a wish



(a) Login (b) Profile (c) Entrance

Figure 2: Wish Wall starts-up

request, can he see the requestor name and contact information. Otherwise, they are covered with XXX at the upper part of the interface.

If none of the candidate users accepted or successfully helped the requestor solve the problem, the platform will re-recommend another N users to support.

3.2 Wish Management

The module manages users wishes being raised and realized. To protect users' privacy, we enforce a life-cycle management policy, which will degrades wish contents until finally they are dropped out of the platform. To better serve the users, statistical aggregation analysis of wishes and wish supports is performed regularly (say, monthly). Its output is fed into the following wish-supporters recommendation module. We leave this work to our further study.

3.3 Wish-Supporters Recommendation

We adopt a hybrid recommendation strategy by combining content-based filtering and collaborative filtering techniques [10, 12].

For each new wish, first we need to filter out top N users as potential wish-supporters. In the background of our system, we have been maintaining a User-Wish Type scoring matrix $R_{m\times n}$, where row i denote user i and column j denote the number of wish of type j that user i has solved. If user i has never solved a wish of type j, that the position (i, j) of the matrix will be '-' .We assume that it can be decomposed into the product of two matrices, and the two matrices are $P_{m\times k}$ and $Q_{k\times n}$, that is

$$R_{m\times n} \approx P_{m\times k} \times Q_{k\times n} = \hat{R}_{m\times n}. \tag{1}$$

where R_{m*n} is the original User-Wish Type scoring matrix, and $Rhat_{m\times n}$ is the estimation of $R_{m\times n}$, which does not contain any missing data. We use the square of the error between the original score matrix and the estimated matrix as the loss function. At the same time, in order to make the model result have better generalization ability, we add a L_2 regular item in the loss function, so the final loss function is

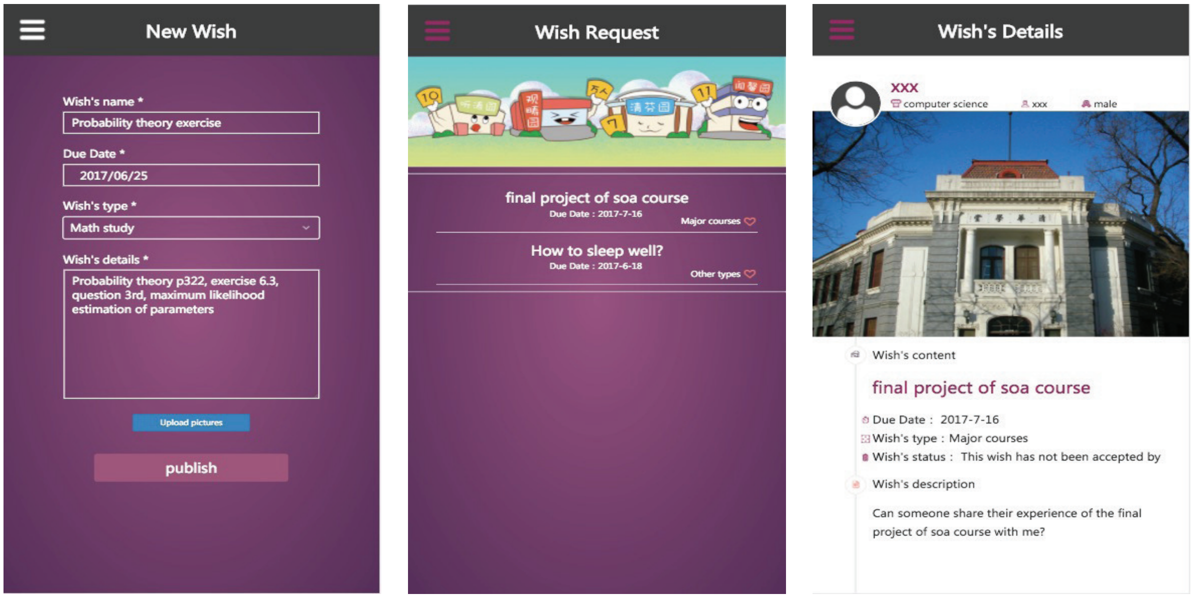
$$E^2_{i,j} = (r_{i,j}-\hat{r}_{i,j})^2 = (r_{i,j}-\sum_{k=1}^{K} p_{i,k}\, q_{k,j})^2 + \frac{\beta}{2}\sum_{k=1}^{K}(p^2_{i,k}+q^2_{k,j}) \tag{2}$$

We want to minimize the sum of the loss of all items that are not missing. That is,

$$min\ loss = \sum_{r_{i,j}\neq -1} E^2_{i,j} \tag{3}$$

The equation can be solved by gradient descent method. Finally, we can get the matrix $P_{m\times k}$ and $Q_{k\times n}$, and therefore we can filter out top 100 users base on the scoring matrix that does not have any missing data.

In the filter above, we only use the historical information that the user resolves the wish. Then we need to use the user's personal information and wish information for further filtering. First of all, we can make further filtering based on user's personal information. There are several important rules that we can learn from our experience: 1. The greater the gap between the user and the wish-makers, the greater the likelihood that he will be able to solve the wish; 2. If the user and the wish-makers come from the same major, user will be more likely able to solve the wish; 3. If the gender of the wish solver is different from that of the wish maker, s/he would prefer to accept the wish; 4. The less the number of wishes that a user is accepting to solve, the greater the likelihood that he will



(a) A new wish raised (b) A list of wishes raised (c) Viewing a raised wish

Figure 3: Wishes from a wish-raiser

accept new wishes. Based on these rules, the following formula can be used to calculate the user i's score in personal information:

$$y_{i_1} = w_1 \cdot \Delta grade_i + w_2 \cdot I_{major=major_i} + w_3 \cdot I_{sex \neq sex_i} + w_4 \cdot \#accept\_wish_i \tag{4}$$

In the upper formula, w_1, w_2, w_3, w_4 are all parameters, which measure the influence of the 4 mentioned factors on the final score. The system in this paper set these parameters to be 0.25, 0.25, 0.25, -0.25. $\Delta grade_i$ indicates the grade gap between user I and the wish-maker. $I_{major=major_i}$ is an indication function, when the major of user and wish-maker is same then equal 1, otherwise 0. $I_{sex} \neq sex_i$ is also an indication function, when the gender of user is different from wish-maker's then equal 1, otherwise 0. $\#accept\_wish_i$ denote the number of wish that user i has accepted to solve.

In addition to using the user's personal information, we also take into consideration the similarity between the new wish and the wishes that users have solved through collaborative filtering. The idea is that if the user ever solved a problem that is similar to the present one, then he should be more likely to be able to solve the new wish now. Use the following formula to calculate the user's score in this area:

$$y_{i_2} = max_{j \in history(i)}\ I_{type=type_j} \cdot Similarity(text_j, text) \tag{5}$$

In the upper formula, $history(i)$ indicates the list of issues that user I has resolved. $I_{type=type_j}$ is an indication function, when the type of $wish_j$ is equal to the type of the new wish then euqal 1, otherwise 0. $Similarity(text_j, text)$ is the text similarity calculation function, which is based on TFIDF numerical statistic method and cosine similarity. In short, through this formula, we want to find out the wish which is most similar to the new wish, from the wish list that user I has resolved, and then use the similarity between them as user's mastery of this type of wish.

Finally, in order to combine the factor from the user's personal information and the similarity factor between the new wish and the wishes that users have solved, we need to combine two results through the following formula:

$$y_i = \beta_1\, y_{i_1} + \beta_2\, y_{i_2} \tag{6}$$

In the formula above, B_1 and B_2 are factors that measure the importance of two results. According to our practical experience, B_1 and B_2 are set to 0.5.

3.4 Implement Details

The background program of our mobile web application is built mainly based on the Flask framework, which is a micro web framework written in Python and based on the Werkzeug toolkit and Jinja2 template engine. Additionally, we use some free Python library such as gensim to finish our sematic processing work during the candidate support users recommendation. What's more, in the Chinese version of our platform, we need to do word segmentation before sematic processing, so we also apply Jieba text segmentation tool in our application.

4 USER STUDIES

Two user studies were conducted to evaluate the wish wall mobile web application. The first user study was conducted in the incipient stage. We did a survey among college students to investigate whether such a platform will be welcomed, and to what extent will be helpful. The second user study was performed after the development, aiming to examine the effectiveness of the platform.

Table 1: Questionnaires in user study I (Likert scale: 1-5 points, 5 for the best and 1 for the worst)

Q1:	Is it a reasonable privacy protection solution by life-cycle management of users wishes on the wish wall platform?
Q2:	Is the wish wall application useful at colleges?
Q3:	How do you evaluate the wish wall functionalities?
Q4:	How do you evaluate the design of the wish wall user interfaces?
Q5:	Do you think the wish wall application can help you cope with some of your real-world problems?

Table 2: Different numbers of users answering Q1 - Q5 in user study I (Likert scale: 1-5 points, 5 for the best and 1 for the worst)

	Answer Q1	Answer Q2	Answer Q3	Answer Q4	Answer Q5
Scale 1	1	3	1	2	3
Scale 2	2	3	3	2	4
Scale 3	1	4	6	5	8
Scale 4	5	4	4	5	1
Scale 5	7	2	2	2	0
Avg.	3.9375	2.9375	3.1875	3.1875	2.4375

4.1 User Study I

Before implementing the wish wall platform, we prepared a questionnaires consisting of 5 questions about the design of its functionalities and user interfaces in order to understand users attitudes towards such a mobile web application 1. 16 volunteer senior students from the department of computer science and technology at Tsinghua University in China participated in the first user study.

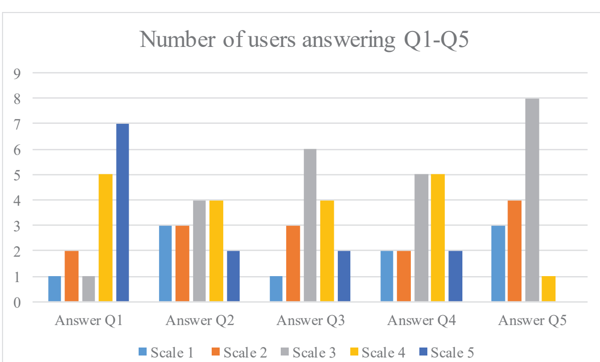


Figure 4: Answer distributions in user study I.

The wish wall platform was well received by the users, whose answers are presented in Table 2 and Figure 4. As seen from the survey result, the average point to each question is a little bit beyond 3, revealing users' pretty positive attitude towards wish wall. As for the first question, the average point from users is 3.9375, which means that the privacy protection mechanism is well accepted by users, they could post any personal questions as they wishes without worrying about privacy disclosure. As for the second question, the average point from users is only 2.9374. This low point, on the one hand, is due to the unreasonable layout and objectives at the very beginning. On the other hand, some users haven't got full understanding of wish wall because our demo development was not fully completed while representing. As for the third and the fourth question, the average point is 3.1875, showing that users are pretty satisfactory with the system's function layout and UI design in the view of engineering. The average point to the fifth question is the lowest (only 2.4375). Based on the score distribution diagram, we can see that users's attitudes are generally moderate or negative. This is mainly because our question-and-answer platform applies novel *online-posted-offline-solved* method and involves in social attributes, which results in some resistance from users.

Table 3: Wishes raised in user study II

Category	Type	Number
Study	Programming	1
	Foreign Language Learning	1
	Dual-Degree Study	1
	Internship	1
Employment	Career Plan	3
Family	Relation of Parents	1
Others		2

4.2 User Study II

The second user study was conducted after the implementation and delivery of the wish wall application. 17 final-year volunteer students from the same university were hired to use the platform on a trial base for about one month.

4.2.1 Distributions of Users Wishes. The users expressed 10 wishes of 12 types in 4 different categories, as shown in Table 3.

Because all the volunteers are senior students, the problems they have encountered in their life are quite similar. Therefore in the testing investigation, the posted questions mainly concentrate on certain aspects, e.g. career planning. The questions relating to career planning occupies over 30%, which are all about how to improve themselves to adapt to the future employment situation. Overall, although those posted questions don't cover all cases, they are quite general.

4.2.2 Realizations of Users Wishes. All posted questions to be solved is the original intention of the platform. Whereas the solving of the question depends on two aspects: the suitable recommendation of question and the solving ability of the recommended.

Imagining the recommending algorithm is implemented based on the function description and algorithm design as discussed above, to examine the effects of recommending, there must be *enough* users. Here *enough* doesn't only indicates users number, but also indicates the variety, which means that users should be from various colleges of campus. More than that, the platform must have collected much

Table 4: Questionnaires in user study II (Likert scale: 1-5 points, 5 for the best and 1 for the worst)

Q1*:	Do you think that the wish wall platform can really help you resole real-world problems?
Q2*:	Are you satisfied with the user interfaces?
Q3*:	Do you think the wish types being supported are sufficient enough?
Q4*:	Are you satisfied with the privacy protection strategy by deleting the realized and out-of-dated wishes?
Q5*:	Do you think the wish wall platform can help you enlarge your social communication scope?

Table 5: Different numbers of users answering Q1* - Q5* in user study II (Likert scale: 1-5 points, 5 for the best and 1 for the worst)

	Answer Q1*	Answer Q2*	Answer Q3*	Answer Q4*	Answer Q5*
Scale 1	0	0	0	0	0
Scale 2	1	1	0	0	1
Scale 3	6	3	3	2	6
Scale 4	7	9	5	7	5
Scale 5	3	4	9	8	5
Avg.	3.7059	3.9412	4.3529	4.3529	3.8235

enough data from users. Both the two conditions are lacked in our user study, so the effects of recommending can't be properly examined. Hence we adopt the cold-start method, i.e. recommend questions to all users.

As for the solving ability of the recommended, because they are in the same age, facing with the similar life stage and problems, they can not provide enough help in some questions, e.g. career planning. We have proposed 10 questions, among which 4 questions were solved, including dual-degree study, programming, relation of parents and foreign language learning. Those questions could be solved within themselves. Other questions, including career planning and trainee consulting, can not be solved within themselves and need help from the experienced senior students. So we can imagine that if the user community are big enough and the user variety is rich enough, much more types of questions could be solved. This is the future expectations of the platform.

4.2.3 Questionnaires and Results. As in user study I, after the experiment, we invited the users to fill in another questionnaires to get to know their experiences with the wish wall platform. Table 4 lists five questions in user study II, and their answers are given in Table 5 and Figure 5.

As seen from the result, the points obtained after development is obviously higher than before. This is mainly because that after the platform has been developed and used, volunteers could understand the platform more directly and deeply, and further gave higher appraisal. The overall average point is around 4, revealing that volunteers are pretty positive about the platform. The average point of question 1 is 3.7059 and the points are between 3 and 4,

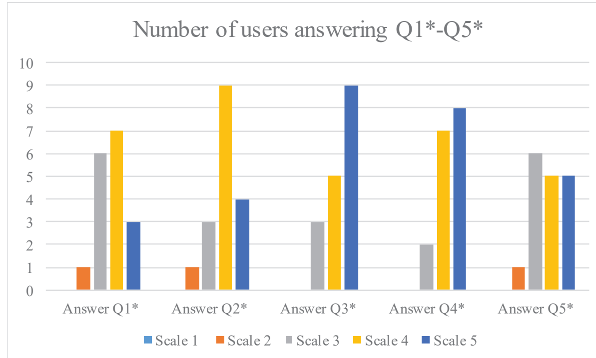


Figure 5: Answer distributions in user study II.

revealing that volunteers think this platform could significantly help them solving problems encountered in campus. The average point of question 2 is 3.9412, which is pretty high but needs further improvement in the user interface design in the future versions of iteration. The average point of question 3 is 4.3529, which is very high, showing that volunteers think the types of problems are rich enough, covering the majority of the problems in campus. The average point of question 4 is 4.3529, which shows that users really accept the privacy protection mechanism used in the platform, this is the base condition in which users could post their thoughts without scruples. The average point of question 5 is 3.8235, which is also pretty high. Through helping each other to broaden social space is one goal of wish wall platform, this demonstrate users' acceptance of the social attributes of the platform.

5 CONCLUSION

The paper reported the design and implementation of a mobile web application called wish wall platform, aiming to facilitate college students to express wishes and support wishes realization by helping each other. In our candidate support users recommendation module, we combine the idea of content-based filtering and collaborative filtering, comprehensively utilizing the user's personal information and the similarity information between the new wish and the wishes that candidate users have solved to enhance our recommendation effect. The performance of the application was evaluated through two user studies. While the result is promising, substantial rooms exist, particularly related to candidate support users recommendation approaches. More in-depth factors like users trust, users preferences, and supporting histories can be taken into account. Statistically analyzing users wish-response for high-quality recommendation could also enable to improve the functionalities of the wish wall platform.

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