A PageRank-based Collaborative Design Team Member Influence Study

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***Abstract*—Aiming at the lack of evaluation indicators of the influence of collaborative design team members, this paper proposes a collaborative design team member influence algorithm DesignRank that combines collaborative design behavior characteristics with PageRank. The DesignRank algorithm takes into account the two factors of self-design level and interactor's design level, and calculates the influence of group members in the collaborative design platform. The experimental results show that the DesignRank algorithm is a more comprehensive and complex method.**

Keywords-collaborative design; member influence; design behavior; PageRank

I. INTRODUCTION

With the rapid development of the Internet, collaborative design platforms such as Tele-Board [1], WiteBoard [2], Miro [3], and Canvanizer have gradually emerged. But these tools usually focus on improving the user's collaborative experience, rather than focusing on the integration of design teaching activities and the participation of members of the collaborative design team in the design process. Therefore, the research team developed a collaborative design platform [4]. Users collaborate in groups to complete design thinking methods and express their opinions by creating sticky notes. At the same time, group members interact in real time by editing, agreeing, and disagreeing other members' post-it notes. In the process of completing the design thinking method, the team members with high influence can effectively organize the design team to carry out design innovation and improve the quality of the design scheme. Besides, find the team members with low influence, understand their problems in the design process, intervene and guide them, which can promote the cooperation of the collaborative design team, and the members of the collaborative team can better design innovation. Therefore, it is particularly important to determine the influence of the members of the collaborative design team through scientific and reasonable methods.

For the research on social influence, scholars' research is mostly conducted on social platforms such as Twitter, forums, and Weibo, and the PageRank algorithm is the most widely used algorithm in social influence research. Tunkelang et al. [5] used the PageRank algorithm to achieve the influence ranking of Twitter users by building a directed graph of Twitter links. Zeynep et al. [6] proposed a personalized PageRank algorithm based on user node behavior and network topology to mine users with high influence on Twitter. Zhai et al. [7] proposed an opinion leader identification algorithm that combines the reply structure of the forum network and the user interest space.

But there are relatively few researches on the influence of members of collaborative design groups. Claros et al. [8] used the interaction behavior of students in the learning process to measure the out-degree, in-degree and centrality to determine the social situation of students in the process of collaborative learning. De Laat et al. [9] calculated the out-degree and in-degree of the communication data of the collaborative members, so as to discover the active and passive participants in the collaborative project. Xu Jingyi [10] determined the core members and edge members in the design process by calculating the point-in and point-out centrality of the interactive behavior of the members of the collaborative design team. Lin Xiaofan [11] used the interaction data of students' comments and messages on Twitter and Facebook, and analyzed the index of point centrality and betweenness centrality to determine the active students and marginal students.

To sum up, the out-degree, in-degree, centrality, etc. in the current research are all calculated based on the number of interactions. However, in the process of collaborative design, only using the number of interactions as a measure cannot fully reflect the degree of interaction and influence of members of the collaborative design team. Because when only the number of interactions is used, the interaction of each collaborative design team member is viewed in isolation, ignoring the fact that members of the collaborative design team are related to each other in the design process. Besides, collaborative design group interactions are essentially the same as interactions on Twitter, forums, and Weibo. During the collaborative design process, group members interact to form a collaborative social network. In this collaborative network, group members can be abstracted as points, and interactions among group members can be abstracted as edges. Therefore, the PageRank algorithm can be used to construct a team member-interaction network to evaluate the influence of the members of the collaborative design team.

Considering the shortcomings of the existing collaborative design team member influence evaluation indicators, this paper comprehensively considers the relationship network characteristics of the collaborative design team and the actual design behavior characteristics of the team members, and proposes a PageRank-based collaborative design team member influence algorithm DesignRank Algorithm. DesignRank Algorithm examines the influence of collaborative design team members in the overall interactive environment.

II. ANALYSIS OF PAGERANK ALGORITHM

In 1998, L. Page and S. Brin [12] proposed the PageRank algorithm to rank Internet pages. The basic idea of this algorithm is to regard all links to the target web page as votes, then all pages containing the target web page link need to assign a part of their PageRank value (PR value for short) to the target web page. That is, the more pages with higher PR

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DOI 10.1109/ISET55194.2022.00012

values point to the target web page, the higher the PR value of the target web page. In order to solve the problem that the calculation of the iterative PR value cannot be converged due to the node out-degree of 0, the webpage with the out-degree of zero can jump to any other webpage with a probability of 1-d. The formula for calculating the PageRank value of the target page is as follows:

$$PR(P) = \frac{1-d}{N} + d\sum_{i=1}^{n} \frac{PR(T_i)}{C(T_i)} \quad (1)$$

Among them, *PR(p)* represents the PR value of the target web page$P$; T_i represents the web page set pointing to the target web page$P$; $C(T_i)$ represents the number of web pages pointing to the target web page$P$; d is the damping factor, and N is the total number of all pages. When the out-degree of a web page is zero, the web page can jump to any other web page with a probability of 1-d.

The traditional PageRank algorithm only focuses on the relationship between nodes, and does not pay attention to other design characteristics of group members, such as the number of post-it notes created, the number of post-it notes agreed, the number of post-it notes disagreed, etc. At the same time, in the collaborative design process, members' influence will only affect the rest of the group, not outside the group.

III. DesignRank algorithm

A. Collaborative Design Behavior Analysis

In the process of collaborative design on the design thinking collaboration platform, each collaborative design team member pays attention to and interacts with each other's design behaviors. Most of their design behaviors are the creation, agreement and disagreement of post-it notes. After a collaborative design team member edits his own opinion by creating a post-it note, the rest of the group can see the opinion immediately, so that subsequent opinions will be influenced by the existing opinion. When members of the collaborative design team agree or disagree a post-it notes during the design process, the post-it note creator will constantly reflect on and optimize the content of the post-it note. Therefore, agreement and disagreement the post-it note will have an impact on the creator of the post-it note. When a collaborative design team member's opinion is agreed and disagreed more, it shows that the member has a high degree of attention, so his influence is higher.

Combining the PageRank algorithm with the design behavior not only meets the requirements for the quantity and quality of the interactors, but also does not break away from the two aspects of the collaborative design team members' interactive behavior and design behavior. This method achieves better results than directly sorting the number of interactors. Moreover, the design behavior of the members of the collaborative design team is regarded as an evaluation index, which grasps the characteristics of collaborative design. Therefore, the influence ranking of the members of the collaborative design team obtained by this method is reliable.

This paper divides the influence index of the members of the collaborative design group into the self-design level index and the interactor's design level index. The self-design level index is comprehensively obtained from the number of post-it notes created by co-design team member, the number of co-design team member agreed/disagreed the number of post-it notes of other team members, the number of co-design team member's post-it notes agreed/disagreed by the rest of the group. At the same time, the design level of the interactor is also related to the real influence of the member. Therefore, it is necessary to consider not only the self-design level of the members of the collaborative design team, but also the design level of the interactors. The member influence index obtained in this way is true, comprehensive and accurate.

B. Self-design Level

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The design behaviors that affect the design level of the members of the collaborative design team mainly include three factors: the number of post-it notes created by co-design team member, the number of co-design team member agreed/disagreed the number of post-it notes of other team members, the number of co-design team member's post-it notes agreed/disagreed by the rest of the group. Different design behaviors have different degrees of influence on the members of the collaborative design team. Therefore, this paper adopts a linear fusion method to combine the three factors that affect the design level of the members of the collaborative design team. In this way, the design level index of the members of the collaborative design team can be obtained, and the calculation formula is as follows.

$$\begin{aligned} \mathrm{Design}Rank\_S(m) = \alpha \times View(m) + \\ \beta \times Comment(m) + \\ \gamma \times Declare(m) \end{aligned} \quad (2)$$

Among them, $DesignRank\_S(m)$ represents the self-design level index of the collaborative design team member m; $View(m)$ represents the number of post-it notes created by co-design team member m; $Comment(m)$ represents the number of co-design team member m agreed/disagreed the number of post-it notes of other team members; $Declare(m)$ represents t the number of co-design team member m's post-it notes agreed/disagreed by the rest of the group; α, β, γ respectively represent the weights of the three design behaviors.

C. Interactor Design Level

When measuring the design level of interactors, not only the number of interactors, but also the design level of the interactors themselves, that is, the number of post-it notes created by interactor, the number of interactor agreed/disagreed the number of post-it notes of other team members, and the number of interactor's post-it notes agreed/disagreed by the rest of the group. The design level index of the interactor is represented by $DesignRank\_F(m)$, which is defined as:

$$DesignRank\_F(m)=\frac{1-d}{N}+ d\sum_{n\in Z(m)}\frac{DesignRank(n)}{Link(n)} \tag{3}$$

Among them, N is the total number of members of the team where the collaborative design team member m belongs. $Z(m)$ represents the set of interactors of group member m. Group member n is an interactor of group member m. $\text{DesignRank}(n)$ represents the influence of group member n. $Link(n)$ represents the total number of group members n interactors. d is the damping coefficient. According to the reference, the default $d = 0.85$, and its meaning is the probability that the user interacts with other users randomly.

D. Implementation of DesignRank Algorithm

The design level of the members of the collaborative design team and the design level of the interactors are combined in a linear fusion method to calculate the influence of the members of the collaborative design team. The DesignRank algorithm is defined as:

$$\text{Design}Rank(m)=\sigma\times DesignRank\_S(m)+ \rho\times DesignRank\_F(m) \tag{4}$$

Among them, $DesignRank(m)$ represents the influence of collaborative group member m, $DesignRank\_S(m)$ represents the self-design level index of group member m, and $DesignRank\_F(m)$ represents the interactor design level index of group member m. σ and ρ represent the weights of self-design level and interactor design level, respectively. The improved algorithm not only takes into account the self-design level and the interactor design level, but also adds weights, which makes the results more reasonable.

The formula (3) can be further decomposed into:

$$DesignRank\_F(m)=\frac{1-d}{N}+ d\sum_{n\in Z(m)}\frac{DesignRank\_F(n)}{Link(n)}+ d\sum_{n\in Z(m)}\frac{DesignRank\_S(n)}{Link(n)} \tag{5}$$

It can be known from formula (2) that $d\sum_{n\in Z(m)}\frac{DesignRank\_S(n)}{Link(n)}$ is a fixed value, and formula (1) converges to a certain constant, so formula (5) converges to a certain constant. Therefore, the improved DesignRank algorithm will converge to a certain constant through repeated iterative calculation, and this constant is the influence of the members of the collaborative design team.

Below is the pseudocode of the DesignRank algorithm.

Algorithm1: DesignRank Pseudocode

Input: Enter the social network graph G of the collaborative design group, and the number of members in the group of each collaborative design member N , ε

Output: Sorted collaborative design team member nodes and influence

```
for g in G: /* Calculate each member's self-design level and initialize Drank for each member*/
  DesignRank_S[g]=α×View(g)+β×Comment(g)+γ×Declare(g)
  DRank[g]=1
for node in G:
  DesignRank_F=0
  for incident_node in G.incidents(node) /* Traverse all members interacting with member node*/
    DesignRank_F+=d*(Drank[incident_node] /len(G.neighbors(incident_node))
  DesignRank_F+=(1.0-d)/N[node]
  aftDrank=σ×DesignRank_S[node]+ρ×DesignRank_F //Calculate the value of DesignRank
  priDrank=DRank[node]//Saves the DesignRank value of the node member from the previous iteration
  DRank[node]=aftDrank
  if |aftDrank-priDrank|<ε
    DRank=Sorted(DRank)// Sort DRank values
    return ranked collaborative design members and DRank values
```

IV. Experiment and Analysis

A. Data Source and Processing

The data used in this paper comes from the collaborative design platform developed by the research team. The platform records the operation behavior of all users through buried points. The research object is 226 students from three courses of Beijing University of Posts and Telecommunications. There are about 64,420 pieces of buried data collected, that is, the user's operation behavior.

Further processing is performed on the collected buried point data. First we extract the interactive behavior data. Through the type field of the buried data, we extract the behaviors of editing others' post-it notes, agreeing others' post-it notes, and disagreeing others' post-it notes. Then we extract the interaction between members. We use a python program to extract the "interaction-interacted relationship" from the OU (Operate User) field and the IN (Interact User) field in the interactive behavior data. After completing the extraction of member interactions, we use the digragh function in the graphviz library to build an interaction graph. After calculating the number of post-it notes created by each co-design team member, the number of each co-design team member agreed/disagreed the number of post-it notes of other team members, the number of each co-design team member's post-it notes agreed/disagreed by the rest of the group, we use a python program to calculate DesignRank.

B. Determination of Parameters

In this paper, AHP (analytic hierarchy process) is used to calculate the parameters. AHP is a multi-criteria, single-objective decision-making method proposed by American operations researcher Saaty [13]. The algorithm realizes quantitative calculation of qualitative events by decomposing the target into multiple sub-targets. First, calculate the α, β, γ parameters in the index of its self-design level. The calculation process of AHP mainly includes three parts.

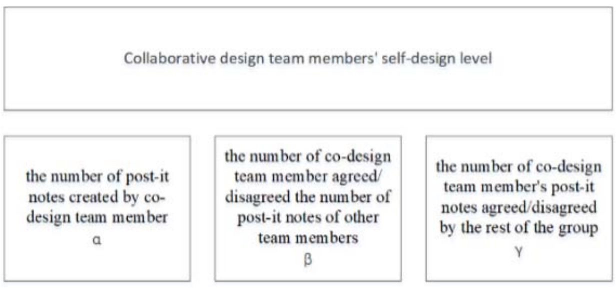

Fig. 1. Hierarchical Model.

a) Build a Hierarchical Model

The hierarchical structure model is shown in Figure 1. The first layer indicates that the purpose is to calculate the design level of the members of the collaborative design team, and the second layer indicates that there are three indicators to influence the criterion layer for target selection.

b) Build a Judgment Matrix

Let the judgment matrix of the design level of the members of the collaborative design team be A_{DU}, in which the element a_{ij} represents the multiple of the importance of the index i to the index j to evaluate the self-design level of the members.

By distributing questionnaires to professional course teachers and taking the teachers' opinions as the consultation results of domain experts, we believe that the first indicator that best reflects the self-design level of the collaborative design team member is the number of post-it notes created by co-design team member., followed by the number of co-design team member agreed/disagreed the number of post-it notes of other team members, and finally the number of co-design team member's post-it notes agreed/disagreed by the rest of the group. Based on this, the judgment matrix A_{DU} of the self-design level of the collaborative design team member is constructed, as shown in formula (6).

$$A_{DU} = \begin{bmatrix} 1 & 3 & 5 \\ 0.33 & 1 & 3 \\ 0.2 & 0.33 & 1 \end{bmatrix} \tag{6}$$

c) Build a weight vector

The construction vector $\omega = (\omega_1, \omega_2, \omega_3)$ is used to represent the weight coefficients of the three indicators.

We use the method root to calculate the judgment matrix, and the normalized weight vector of the judgment matrix A_{DU} is obtained as $\omega = (0.637, 0.258, 0.105)$. Therefore, $\alpha = 0.637$, $\beta = 0.258$, $\gamma = 0.105$.

In the same way, we can use the AHP to calculate, the self-design level weight $\sigma = 0.250$, and the interactor design level weight $\rho = 0.750$.

C. Result Analysis

Using the data collected by the collaborative design platform, and using the DesignRank algorithm described in the previous section, we calculated the DesignRank value of each collaborative design team member and compared it with the number of interaction methods. Table I lists the details of the top 10 collaborative design team members on DesignRank.

TABLE I. THE DESIGNRANK VALUE OF THE COLLABORATIVE DESIGN TEAM MEMBERS IS COMPARED WITH THE SELF-DESIGN LEVEL, THE INTERACTOR DESIGN LEVEL, AND THE NUMBER OF INTERACTIONS

Collaborative member	**Self-design level**		**Interactor design level**		**Number of interactions**		**Collaborative design team member influence**	
	The value of self-design level	*Ranking*	*The value of interaction design level*	*Ranking*	*The value of the number of interactions*	*Ranking*	*The value of DesignRank*	*Ranking*
cyh	46.711	1	19.784	1	3	79	22.563	1
wsh	6.249	70	14.557	2	3	79	16.413	2
hyl	20.683	3	11.247	4	2	35	13.597	3
zc	20.03	5	9.737	8	5	1	12.3	4
ch	28.133	2	6.666	33	3	79	12.011	5
mzy	11.034	31	11.978	3	2	35	11.743	6
zqy	14.482	16	10.215	8	5	1	11.278	7
oyaf	15.806	14	9.507	10	2	35	11.075	8
gx	9.975	41	11.357	4	2	35	11.013	9
wly	20.368	4	7.744	20	5	1	10.887	10

The size of the DesignRank value represents the influence of each collaborative design member in this group. From the calculation method of the DesignRank algorithm, we can see that there are two main factors that affect the DesignRank value: the self-design level of the collaborative design team members; the interactor design level. Because the DesignRank value is calculated differently from the self-design level and the interactor design level, the DesignRank value of a member of the same collaborative design team in Table I is inconsistent with the self-design level and the interactor design level. Comparing the change trend of the same collaborative design team member's DesignRank value, self-design level, interactor design level, and the number of interactions, it can be found that the rankings of the DesignRank value, the self-design level, the interactor design level and the number of interactions are not the same, as shown in Figure 2.

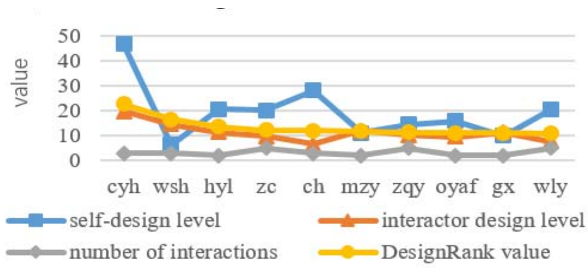

Fig. 2. Comparison of the change trend between the DesignRank value, the self-design level, the interactor design level, and the number of interactions

There are similarities in the changing trends of the same collaborative design team member's DesignRank value, self-design level and interactor design level: the three trend lines are all downtrends, indicating that on the whole, the change trends of the DesignRank value, the self-design level and the interactor design level are similar. Collaborative design team members who perform better in one of these areas also tend to perform better in the other two. As far as a single collaborative design team member is concerned, the fluctuation is relatively large, as can be seen from Figure 3: at the same data point, except for a few members of the collaborative design group who performed well on all three indicators, the performance of other members was inconsistent. For example, cyh ranked first in both indicators, and hyl and zc did not have much difference in performance in the three indicators. But in addition, many collaborative design team members have different performances on the two indicators of their self-design level and the interactor design level. The self-design level of wsh, mzy, and gx is not high, but the design level of the team members who interact with them is high, so the DesignRank value is better. It is precisely because a variety of factors are considered in the calculation of DesignRank, the results of ranking the influence of collaborative design team members based on the DesignRank value may be different from the ranking results based on the number of interactions.

To sum up, DesignRank is a more comprehensive and complex measurement method. Since other methods consider a single indicator, such as only considering the number of interactions, the DesignRank value considers more factors and the calculation is more complex, so it is more comprehensive.

V. Summary and Prospect

In this paper, a PageRank-based collaborative design team member influence algorithm DesignRank is proposed, which comprehensively considers collaborative design behavior characteristics and reflects the position and influence of collaborative design members in the design team. DesignRank comprehensively considers a variety of factors: self-design level (represented by the DesignRank_S) and interactor design level (represented by DesignRank_F). This makes the influence of collaborative design team members under the DesignRank algorithm more reflective of their combined influence. However, the collaborative design members selected in this paper are all design beginners. In the following research, we will select relatively professional design members for research, and continue to look for other factors related to the influence of collaborative design team members, so as to conduct a more comprehensive exploration of the methods to be studied.

Acknowledgment

This work is supported in part by 2019 Outstanding Innovative Education Team in Beijing Universities - New Engineering Engineering Professional Cognition and Innovative Quality Training and Education Team, in part by 2020 Beijing Higher Education "Undergraduate Teaching Reform and Innovation Project" - Research on Independent Learning Evaluation Indicators of Innovation and Entrepreneurship Education.

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