Organizational Churn: A Roll of the Dice?

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Introduction

Network science has gained popularity in management science, and modeling a human resource organization is—at root—modeling its networks. In this problem, we focus on a specific phenomenon—churn—in the Information Cooperative Manufacturing (ICM) organization.

We decompose the problem into several steps:

- Build a human capital network structure using the information provided, and use it as the framework for further analysis.
- Design a model capturing the mechanism of the churn effect and design reasonable responses by the human relations (HR) manager.
- Estimate organizational productivity and costs.
- Analyze sustainability of the network under different churn rates, and estimate its effects.
- Set up measures of health of the company and test effects on it of various changes. Devise heuristics for the HR manager accordingly.
- Incorporate ideas from team science into the model and point out the possibilities of analyzing from a multilayer view.
- Implement tests of sensitivity and analyze the model's strengths and weaknesses.

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Fundamental Assumptions

- No staff naturally retire or get fired. Each staff member makes a monthly decision whether to leave or not.
- The staff members have latent characteristics unknown to the HR manager (and us) that might influence their decisions.
- Beyond the visible organizational structure, there exists an information network.
- Each staff member's monthly decision (to leave or to stay) acts as a piece of information that flows through the human capital network.
- Individuals digest received information through a learning process, and this learning mechanism affects their decisions.
- The HR manager can affect the number of people in positions via a strategy for promotion and recruitment.

Preliminaries

The Information Network

Assigning Levels to Staff

We merge the table and graph given in the problem statement by assigning position levels to entries in the organizational chart, based on several reasonable assumptions:

- Every senior/junior manager has a clerk for administrative tasks.
- The position level of a staff member tends to be higher the closer the office is to the CEO in the organizational graph.
- The position level of a manager cannot be lower than someone whose office is in a lower tier in the organization graph.

We can get the allocation shown in **Table 1** for the 370 positions.

Constructing the Human Capital Network

We construct a graph G. Let $V(G) = \{v_1, \ldots, v_{370}\}$ be the nodes of the network, with each position having a corresponding node. Let $E(G)$ be the edges in the network, with $(v_i, v_j) \in E(G)$ if at least one of the following holds:

- i and j are in the same office, i.e., in the same box in the organizational chart.

Table 1.

The distribution of staff by position.

Tier	Position \ Level	1	2	3	4	5	6	7	Total
1	CEO	2	0	0	0	0	0	2	4
2	Research	1	0	0	0	2	0	1	4
	CIO	1	2	0	0	8	0	3	14
	CFO	1	2	0	0	8	0	3	14
	HR	0	1	0	0	2	0	1	4
	VP	2	0	0	0	0	0	2	4
	Facilities	1	0	0	0	2	0	1	4
	Sales Marketing	1	0	0	0	2	0	1	4
3	Networks	0	1	1	0	11	0	1	14
	Information	0	1	1	0	11	0	1	14
	Program Manager	0	1	1	0	6	5	1	14
	Production Manager	1	1	0	0	10	0	2	14
	Plant Blue	0	1	1	0	6	5	1	14
	Plant Green	0	1	1	0	6	5	1	14
	Regional	0	1	1	0	6	5	1	14
	World Wide	0	1	1	0	6	5	1	14
	Internet	0	1	1	0	6	5	1	14
4	Director	0	6	6	0	6	0	6	24
5	Branch	0	0	11	25	12	120	0	168
	Total	10	20	25	25	110	150	30	370

Key to levels:
*1: Senior Manager 2: Junior Manager 3: Experienced Supervisor
4: Inexperienced Supervisor 5: Experienced Employee
6: Inexperienced Employee 7: Administrative Clerk

- i is the head of an office and j is the head of the office directly above, or vice versa. We consider the staff member who has the highest position level in an office to be the head of the office, such as a junior manager in the Networks office or an experienced supervisor in a Branch office.
- i and j are both senior managers.

We visualize this network in **Figure 1**.

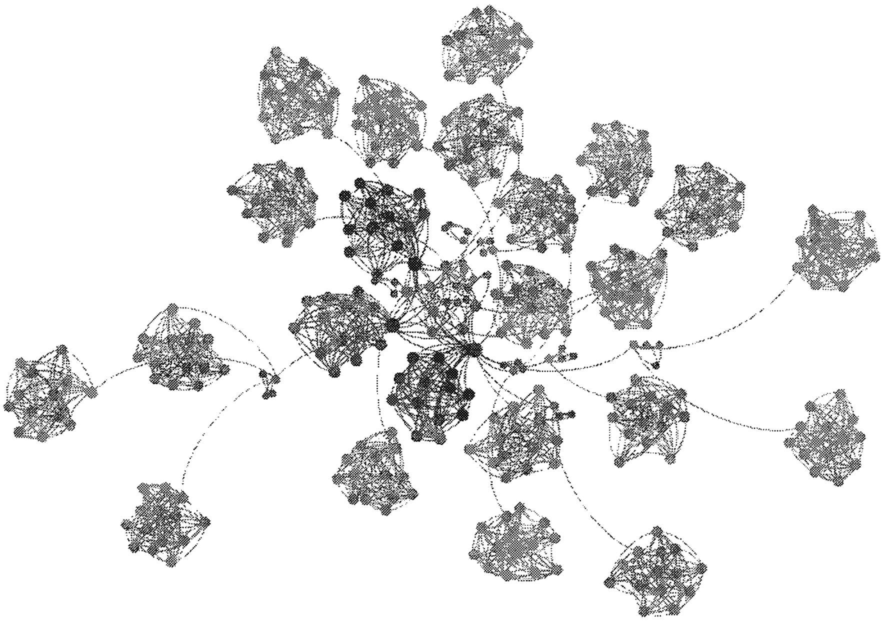

Figure 1. Information network in ICM.

Terms and Mathematical Notations

- **Level:** Position level, such as manager, supervisor, or employee.
- **Abbreviations:** We assign each level an abbreviation: **SE:** Senior Executive, **JE:** Junior Executive, **ES:** Experienced Supervisor, **IS** Inexperienced Supervisor, **EE:** Experienced Employee, **IE:** Inexperienced Employee, **AC:** Administrative Clerk.
- t: Time is discrete and measured in months.
- $\Omega^{(t)}$: The set of people who leave the company at the end of month t.
- $\Theta^{(t)}$: The set of people recruited at the beginning of month t.
- $\Gamma^{(t)}$: The set of employees, after recruitment, at the beginning of month t.
- $f^{(t)}$: The mapping from $\Gamma^{(t)}$ to $V(G)$, which maps individual $i \in \Gamma^{(t)}$ to position $f^{(t)}(i) \in V(G)$ at time t. $\left[f^{(t)}\right]^{-1}$ is the inverse mapping.
- $d(u, v)$: The distance (length of the shortest path) between nodes (positions) u and v.
- $d_{ij}^{(t)}$: The distance between two individuals $i, j \in \Gamma^{(t)}$ at t, defined by $d\big(f^{(t)}(i), f^{(t)}(j)\big)$.

Models

We construct a probabilistic model of the dynamic processes of staff churn, promotion, and recruitment. Our model is inspired by Bayesian learning principles. Bayesian learning has been used to analyze information aggregation in social networks [Acemoglu et al. 2011], in which individuals modify their decision based on previous outcomes of other individuals in the network.

We use the Bernoulli and beta distributions to estimate and update the likelihood of an individual leaving. We use the beta distribution because it is the conjugate prior of the Bernoulli distribution; for information on conjugate distributions, please refer to Bishop [2006].

Modeling Staff Churn

Preliminaries

For the sake of explaining our intuition, consider a simple Bayesian learning process. Suppose that a random variable $u \in \{0, 1\}$ is drawn from a Bernoulli distribution, where p is unknown:

$$u \sim \text{Bernoulli}(u; p) = p^u (1-p)^{1-u}.$$

Assume that an observer wants to estimate the parameter p by drawing multiple instances of u. The individual has a prior estimation $f(p)$ for p, which we describe by a beta distribution

$$f(p) = \text{Beta}(p; \alpha, \beta) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{\text{B}(\alpha, \beta)},$$

where $\text{B}(\alpha, \beta)$ is the normalization constant. After seeing an outcome of $u = 1$, the observer updates the prior according to Bayes' formula (for simplicity, we ignore the normalization constants):

$$f(p) \propto \left(p^{\alpha-1}(1-p)^{\beta-1}\right) \cdot p \sim p^{\alpha}(1-p)^{\beta-1},$$

which can be viewed as increasing α by 1. Similarly, if an outcome of $u = 0$ is seen, the observer increases β by 1. As the number of observations tends toward infinity, we have $\alpha/\beta \to p$ and the beta distribution tends to the Dirac delta function $\delta(x - p)$, a result indicating that the observer's estimation converges to p regardless of the original prior distribution on p.

Modeling the Churn Rate

We model the churn rate in a way conceptually similar to a Bayesian learning process. Specifically, we view leaving a position as a decision-making process: An individual i decides whether to *leave* or to *stay* in a particular month t based on a random variable $u_i^{(t)} \in \{0, 1\}$, where 0 indicates *leave* and 1 indicates *stay*.

We draw $u_i^{(t)}$ as follows:

- We assume for i two hyperparameters $\alpha_i^{(t)}$ and $\beta_i^{(t)}$.
- We draw $p_i^{(t)} \sim \text{Beta}(\alpha_i^{(t)}, \beta_i^{(t)})$.
- Then we draw $u_i^{(t)} \sim \text{Bernoulli}(p_i^{(t)})$.
- Finally, we determine that i is to *stay* if $u_i^{(t)} = 1$, and otherwise to *leave*.

Integrating out the random variable $p_i^{(t)}$, we find that the distribution of $u_i^{(t)}$ is an instance of the beta-binomial distribution, with mean and variance

$$\mu = \frac{\alpha}{\alpha + \beta}, \qquad \sigma^2 = \frac{\alpha\beta}{(\alpha + \beta)^2}.$$

This result has some nice properties for modeling the churn process:

- On the one hand, we can easily estimate i's probability *to leave* as

$$\frac{\beta_i^{(t)}}{\alpha_i^{(t)} + \beta_i^{(t)}}.$$

- On the other hand, an increase in α_i decreases i's tendency to *leave*, while an increase in β_i increases the tendency to *stay*.

However, three problems remain:

- How to determine the prior α_i and β_i?
- How to update the hyperparameters?
- How to take the network structure into account?

We will explain these problems in the following paragraphs.

Determining the Prior We can easily model the effect of an annual churn rate of p per year by setting $\beta/(\alpha + \beta) = p/12$. We further observe that the variance of the beta distribution is

$$\frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)},$$

so that a larger $(\alpha + \beta)$ leads to a smaller variance, indicating better estimation of p and more knowledge about the company's status. Thus, it is safe to assume that people at high-level positions have a larger $(\alpha + \beta)$ compared to others, and that their decisions are less volatile.

Updating $\alpha_i^{(t)}$ and $\beta_i^{(t)}$ An individual is more likely to leave if that individual is connected to others who have left. This can be described as a learning process for the individual: Each month, the individual observes the decisions made by others in the previous month. For every observation of "to stay," individual i increases α_i; for every observation of "to leave," the individual increases β_i. We normalize the update values, so that every month an individual's $(\alpha + \beta)$ increases by 1.

Information Reduction From an individual's perspective, the resignation of someone in the same department should have a greater impact than that of someone in another department. We take this into account by reducing the update value of the hyperparameters: We reduce the update of 1 by a factor of $1/d^2$ if the information takes d steps to transmit.

An Algorithm for the Churn Model

We give an algorithm for this process. For every individual i:

- Sample the churn result for month t using hyperparameters $\alpha_{i,t}$ and $\beta_{i,t}$, and determine whether i stays or leaves.
- If i decides to stay, initialize the two variables $\hat{\alpha}$ and $\hat{\beta}$ to 0.
- For every individual j in $\Gamma^{(t)} \backslash \Theta^{(t)}$ (individuals who stay), update

$$\hat{\alpha} = \hat{\alpha} + \frac{1}{\left(d_{ij}^{(t)}\right)^2};$$

- For every individual j in $\Omega^{(t)}$ (individuals who leave), update

$$\hat{\beta} = \hat{\beta} + \frac{1}{\left(d_{ij}^{(t)}\right)^2}.$$

- Update: $\alpha_i^{(t+1)} = \alpha_i^{(t)} + \dfrac{\hat{\alpha}}{\hat{\alpha} + \hat{\beta}}$, and $\beta_i^{(t+1)} = \beta_i^{(t)} + \dfrac{\hat{\beta}}{\hat{\alpha} + \hat{\beta}}$.

Modeling HR Manager's Reactions

Since recruiting for a higher-level position usually requires more time and money compared to promoting a lower-level staff member and then recruiting for that vacancy, an HR manager would always prefer promoting to recruiting whenever possible. This principle allows us to consider these two aspects separately.

Promotion Models

We summarize some basic rules for promotion:

- The HR manager does not read annual evaluation reports, hence does not know anything about the matching of staff to positions. Consequently, the HR manager does not consider changing staff within the same level.
- The first choice for a vacancy is to promote someone who has the amount of experience required. If no person is qualified and recruiting resources permit, the HR manager posts notice of an opening.
- If while the opening remains posted, some employee's experience reaches the required amount, the HR manager promotes the person and cancels the opening.
- The HR manager never promotes an administrative clerk, because recruiting an inexperienced employee is cheaper and less time-consuming than recruiting a clerk.

The HR manager has no knowledge about the capabilities of any employee, nor their probability of leaving. Therefore, to make the promotion process *fair*, the HR manager should choose the employee on the next lower level with the longest working experiences. Hence, we have the following strategies:

Experience-Oriented For a vacancy on level l $(l < 6)$, select the employee on level $l+1$ with the longest experience; the employee should also satisfy any other promotion requirements. If nobody is available, start recruiting.

If the HR manager happens to know the churn model previously described and can make inferences about the probability of individuals leaving, then there can be a slight improvement:

Dissatisfaction-Oriented For a vacancy on level l $(l < 6)$, select the employee most likely to leave (the one with the highest β/α ratio) among all the employees on level $l+1$ who satisfy the promotion requirements. If nobody is available, start recruiting.

The HR manager can also take the human capital network structure into consideration by promoting the employee with the largest centrality.

Centrality-Oriented For a vacancy on level l, select the employee with the largest closeness centrality(tends to be greater when the employee is in the middle of the network) from qualified employees on level $l+1$. If nobody is available, start recruiting.

Recruitment Models

We make the following assumptions about the recruiting strategies:

- The HR manager has a limited effort for recruiting, in terms of number of vacancies to recruit for at one time. This limit still holds when there is a vacancy in the HR office itself.
- When the number of vacant positions is higher than the limit, the HR manager ranks the vacant positions from higher level to lower level and

concentrates on recruiting for the positions at the highest levels. For example, the HR manager would prioritize recruiting a manager over recruiting an employee.

- The HR manager renews the list of vacancies only every so often, e.g., quarterly or semi-annually.

Thus, the HR manager has two direct means to increase the recruitment rate:

- Increase the resource limits, so that more positions can be recruited for at one time; or
- increase the frequency of renewing the list of vacancies.

Also, the HR manager can control the promotion rate by setting different thresholds for promotion, which is an indirect method of controlling recruitment.

Model Functions

Our models already encompass a large variety of the mentioned features of ICM, including:

- The information web captures how "churn" diffuses among staff members.
- The risk of churn can be identified at an early stage by observing each staff member's β/α. The higher β/α, the more likely the staff member chooses to leave.
- The resignation of a staff member increases the β parameter of other employees, thus increasing their chance of leaving.
- We cover the fact that churn rates for middle managers are higher than other levels of positions by allowing different priors (different values of the parameters α and β) for different levels.
- The HR manager can control the recruitment flow with choice of recruitment effort, recruitment time period, and promotion threshold.

Matching staff members to positions is one aspect that our model does not encompass. However, it could be incorporated by adding more assumptions about the staff's skill classifications.

Simulations

Added Assumptions for Simulations

We make further assumptions in setting values for parameters used in our simulations:

- The required experience for promotion, in months, are (from higher levels to lower) are 48, 48, 24, 24, 12, 0.
- The time period for updating recruitment postings is 6 months.
- The $\alpha + \beta$ for different levels of positions are (from higher levels to lower level) 144, 120, 64, 48, 32, 24, 24.
- The maximum recruiting effort for the HR manager is 9% of the 370 positions (an average of 8%–10%).
- All the data given regarding recruiting time, recruiting cost, annual salary, and training cost are deterministic.

Task 1: Simulations under Current Situation

We first present our basic simulation results of the current situation. **Figure 2** shows the churn rate for the different levels of position based on 50 simulations. The churn rate of middle-managers (JE, ES and IS) is roughly 30%, and the churn rate for other positions (SE, EE, IE and AC) is around 15%. The overall churn rate of the company is relatively stable at 18%, which corresponds to the current situation at ICM.

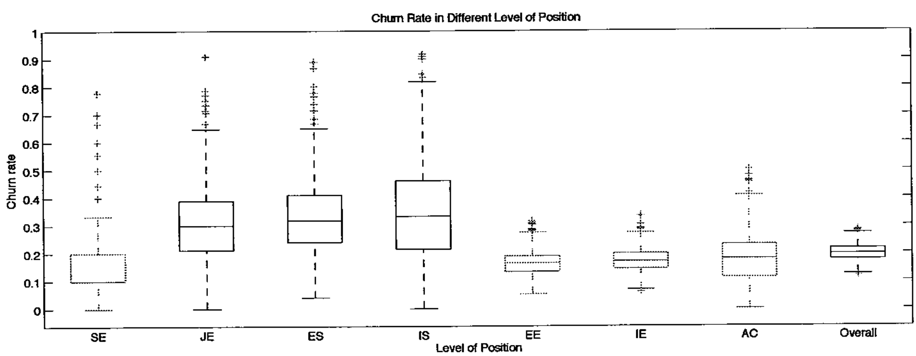

Figure 2. Churn rates for the different levels.

Another feature of ICM is that the churn rate is steadily increasing. The simulation result in **Figure 3** exhibits such a trend from 18% in the first year to 20% in the fifth year.

Task 2: Defining Productivity and Testing Churn Influences

A metric to measure the company's organizational productivity should incorporate the following three aspects:

- **Position level** People at different levels surely make different contributions to the overall performance of a company. We reasonably assume

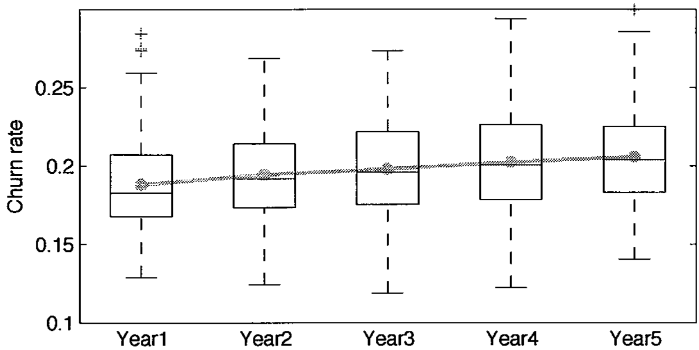

Figure 3. Overall churn rates over the next five years.

that the relative average annual salary $S_i^{(t)}$ at individual i's level reflects i's contribution.

- **Training experience** Experience in the current position contributes to one's productivity. We use as a proxy for experience the total training cost spent on an individual since the start of the individual's working in the current position, denoted by $T_i^{(t)} t_i^{(t)}$.
- **Dissatisfaction** An individual more unsatisfied with their current situation tends to work less inefficiently, leading to lower productivity. We calculate i's dissatisfaction $\sigma_i^{(t)}$ as

$$\sigma_i^{(t)} = \sum_{\tau=t-t_i^{(t)}+1}^{t-1} \left\{ e^{[-\tau-(t-1)]} \sum_{j\in\Omega^{(\tau)}} \frac{1}{d_{ij}^{(\tau)2}} \right\}.$$

We want to incorporate the effect of dissatisfaction, using an expression that is monotonic but not fast increasing. The easiest way to construct such an expression is to use the logarithm function. To increase the degree of freedom and make the model more flexible, we also add a parameter δ.

So we normalize $\sigma_i^{(t)}$ to

$$\frac{1}{1+\delta \ln\left(1+\sigma_i^{(t)}\right)},$$

where δ is a parameter reflecting the influence of dissatisfaction. We set $\delta = 0.1$ for now; we carry out sensitivity analysis regarding it later. The exponential in this expression represents the decline of memory, reflecting the fact that people tend to forget past events [Ebbinghaus 1913].

Incorporating the three components, the productivity of an individual i at time t is

$$p_i^{(t)} = \frac{S_i^{(t)} + T_i^{(t)} t_i^{(t)}}{1 + \delta \ln\left(1 + \sigma_i^{(t)}\right)}.$$

To calculate organizational productivity, we use a weighted sum of individuals' productivity. The weight $w_i^{(t)}$ is determined by an information network structure; an individual in an important position "weighs" more. Here we use *closeness centrality* to reflect this importance. So organizational productivity is defined by:

$$P^{(t)} = \sum_{i \in \Gamma^{(t)}} w_i^{(t)} * p_i^{(t)} = \sum_{i \in \Gamma^{(t)}} p_i^{(t)} \sum_{v \in V(G) \setminus \left[f^{(t)}\right]^{-1}(i)} \frac{d\left(v, \left[f^{(t)}\right]^{-1}(i)\right)}{370 - 1}$$

Using this measure, we can track dynamic change in organizational productivity. We can distinguish two kinds of effect associated with an individual's leaving:

- **Direct Effect** $\mathrm{DE}^{(t)}$ The loss of the productivity of the individual who left.
- **Indirect Effect** $\mathrm{IE}^{(t)}$ The loss of productivity caused by the increased dissatisfaction of the remaining staff after the resignation.

We set

$$\mathrm{DE}^{(t)} = \sum_{i \in \Omega^{(t)}} w_i^{(t)} p_i^{(t)}$$

$$\mathrm{IE}^{(t)} = \sum_{i \in \Gamma^{(t)} \setminus \Omega^{(t)}} w_i^{(t)} \left(\frac{1}{1 + \delta \ln\left(1 + e^{-1} \sigma_i^{(t)}\right)} - \frac{1}{1 + \delta \ln\left(1 + \sigma_i^{(t+1)}\right)} \right) \times \left(S_i^{(t)} + T_i^{(t)} t_i^{(t)}\right).$$

We calculate the loss of organizational productivity associated with a person's leaving and decompose it into direct effect and indirect effect. We run 50 simulations for the next five years and average the results for presentation in **Figure 4**.

Both the direct and indirect effects on organizational productivity closely track the number of staff who leave. An individual's resignation causes about a 20-unit direct effect and a 25-unit indirect effect. Total organizational productivity is 2000–2500 units monthly, so a person leaving costs 2% of total organizational productivity.

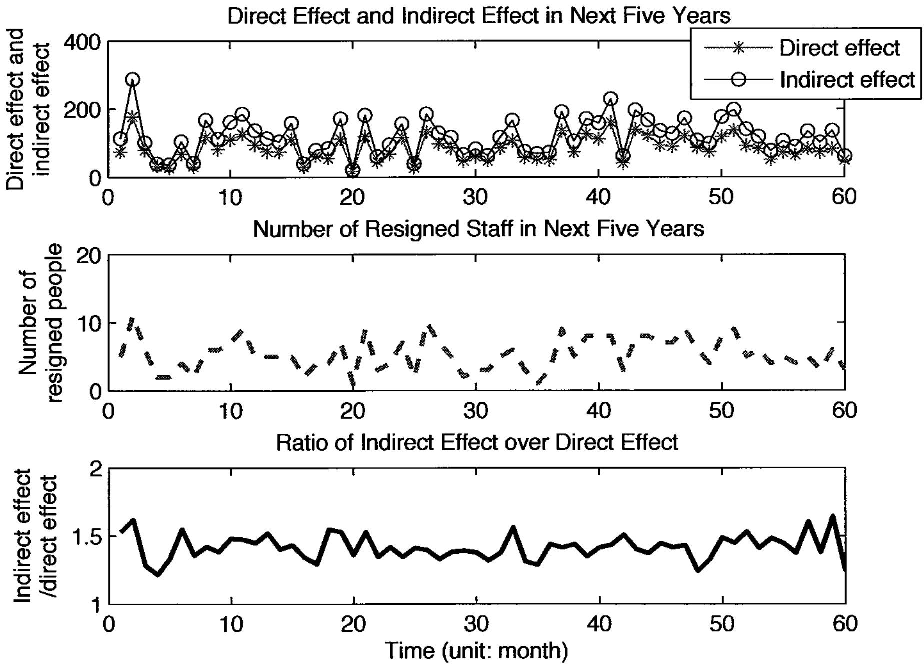

Figure 4. Effect on organizational productivity.

In the simulations, the indirect effect is larger than the direct effect, with a stable ratio. The parameter δ can reflect how a person views the resignation of another individual, and we will return to it later.

Task 3: Budget Calculation

We consider the company's budget for human capital. The budget consists of three components: staff salaries, recruitment cost, and training cost. To make the calculation easier, we continue to assume that all individuals at the same position level have the same salary and training cost, and that recruitment cost is uniform in each position level. We assume that all costs are incurred uniformly across the corresponding time span.

We run simulations of the company and show the calculated costs in **Figure 5.**

The costs presented in **Figure 5** are calculated every six months. On average, the recruitment cost is 7σ and the training cost is 37σ. However, those are only a small fraction of total cost, since salaries account for the largest part.

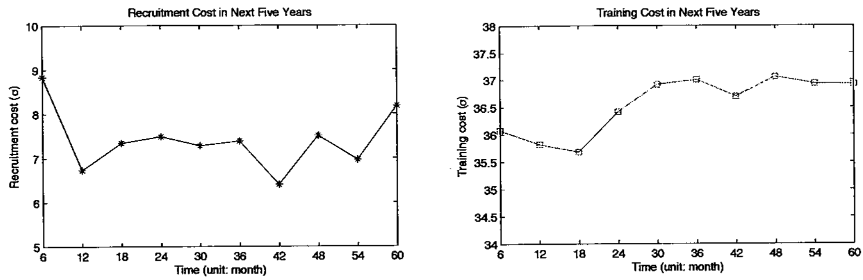

Figure 5. Budget calculation for next five years.

Task 4: Changing the Churn Rate

We run simulations of ICM under churn rates of 18%, 25%, and 35%. To achieve these "goals," we simply adjust the β/α ratio: For a churn rate of 25% per year, we let $\beta/\alpha = 0.25/12 = 0.02083$; for 35% per year, we let $\beta/\alpha = 0.35/12 = 0.02916$.

We run 50 simulations under each churn rate and take the averages. **Figure 6** shows our results.

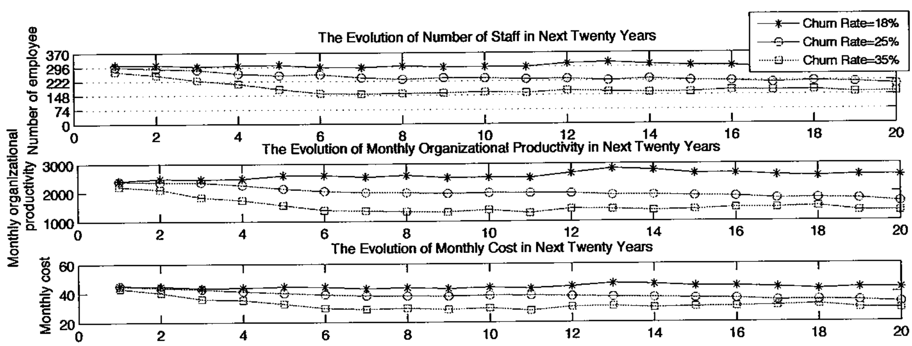

Figure 6. Evolution of ICM—number of employees, productivity, and monthly cost—over 20 years, at churn rates of 18%, 25%, and 35%.

The line charts reflect the evolution of the number of staff, monthly organizational productivity, and monthly cost over the next 20 years under different churn rates. At 18% churn rate, the company sustains 80% of its positions (around 300 staff members) over a long time span. However, at the higher churn rates, staff size declines dramatically during the first six years, then stabilizes, to 60% of the 370 positions for 25% churn and 40% for 35% churn. We can do a rough validation of the results by observing that at each churn rate, the recruitment rate too stabilizes; thus, the stable percentage of employees at a 35% churn rate should be around $80\% \times 18/35 \approx 42\%$.

Under a high churn rate, more people leave the company, leading to both higher direct and indirect effect. Organizational productivity decreases by around 30% (for 25% churn) and 50% (for 35% churn).

Although high churn rates incur higher recruitment cost, that cost is minor compared with the large decline in salary and training costs resulted from having fewer staff. Total cost decreases by nearly 20% (for 25% churn) and 40% (for 35% churn).

To sustain staffing, the HR manager should change the recruitment strategy. If we change just the churn rate, the number of employees will gradually change. We need to take into account also the recruitment effort, so as to keep the total number of employees constant. The simulations above assume that the time period for updating recruitment post is 6 months and recruitment effort is 9%. Now we change these two parameters to fill the gap more quickly. We change the updating interval to 4 months and the recruitment effort to 8.3% under 25% churn rate, and 3 months and 9% under 35% churn rate. **Figure 7** shows the distribution of the results from 10 simulations.

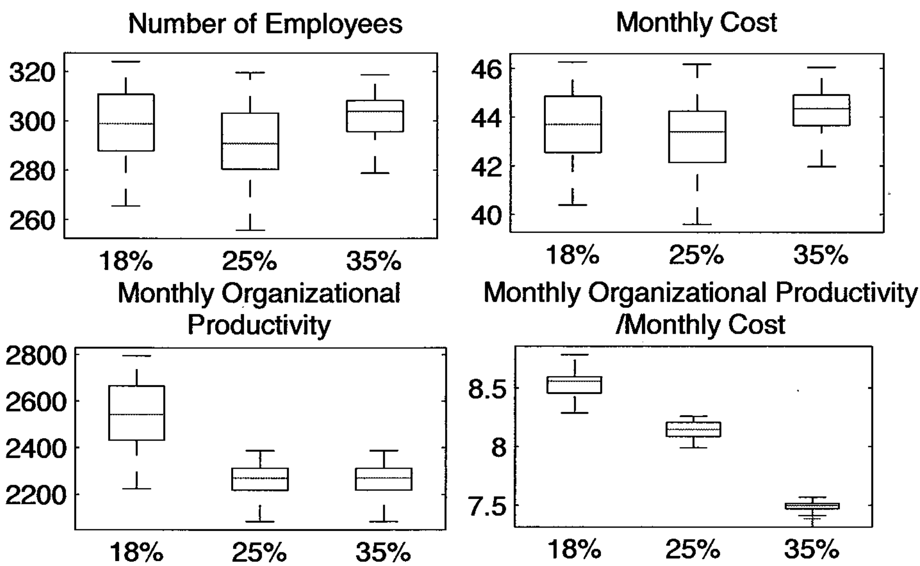

Figure 7. Comparison of consequences of new recruitment strategy for different churn rates.

Under the new recruitment strategies, ICM can sustain roughly 80% staffing with no significant change in monthly cost. However, organizational productivity varies a lot. It decreases by more than 10% under either high churn rate, even if the staff numbers remain the same. If we use organizational productivity per unit cost as an indicator of the company's efficiency, we can see from the boxplot at lower right that the company runs more efficiently under a lower churn rate.

Task 5: Effect of No External Recruiting

We apply our methodology to identify the impact of no external recruiting. Our focus is on the number of employees in each office. We allow only churn and promotion, and estimate the percentage of the employees in the offices. For better estimation, we assume a uniform probability distribution of the years of experience for the employees, so that one-fourth of the employees in each level are qualified for promotion.

Offices in tiers 1 and 2 sustain good levels of staffing, whereas offices in lower tiers suffer significant reductions. This conclusion is rather counterintuitive at first sight, since middle managers tend to have a higher churn rate; but it is quite plausible, given that low-level positions are not filled, whereas high-level positions can be sustained by promotion.

The number of remaining employees after two years is around 204, equal to the theoretical value that we calculate: The number of employees in year 0 is 370×0.85. Assuming that the proportion of employees in different positions remain constant, the proportion of employees leaving ICM each year is

$$\frac{325 \times 0.18 + 45 \times 0.30}{370}.$$

Therefore, after two years we have

$$370 \times 0.85 \times \left(\frac{1 - (325 \times 0.18 + 45 \times 0.30)}{370} \right)^2 \approx 204.$$

Comparing Strategies

Currently, when deciding who to promote among qualified candidates, the HR manager chooses the one with the longest working time (*Experience*). We consider two other ways discussed before: selection by centrality within the information network (*Centrality*) and selection by likelihood to leave (*Likelihood*). We still use closeness centrality defined in previous sections.

Table 2 compares promotion strategies. The staff number declines under all three strategies, which is consistent with the steadily increasing churn rate. But the number of employees under *Likelihood* strategy is 2.6% higher after 10 years than under *Experience*. Besides, both *Centrality* and *Likelihood* strategies increase organizational productivity by more than 11% in Year 10. So changing the promotion strategy can contribute to the improvement of human capital management.

Table 2. Comparison of promotion strategies.

Strategy		Year 2	Year 4	Year 6	Year 8	Year 10
Experience	Employees	313	311	305	299	293
Centrality	Employees	311	308	302	296	290
	Increase (%)	−0.6%	−1.0%	−0.9%	−1.0%	−1.0%
Likelihood	Employees	311	309	308	304	301
	Increase (%)	−0.6%	−0.5%	**1.2%**	**1.6%**	**2.6%**
Experience	Productivity	2575	2706	2699	2652	2613
Centrality	Productivity	2589	2789	2879	2897	2917
	Increase(%)	0.6%	3.1%	**6.7%**	**9.3%**	**11.6%**
Likelihood	Productivity	2578	2759	2873	2886	2904
	Increase (%)	0.1%	2.0%	**6.5%**	**8.8%**	**11.1%**

Task 6: Team Science and Multilayers

To fulfill the HR manager's vision, we apply team science and discoveries from multiplayer network research.

Incorporating Team Science

Recent studies on team performance point out many ways to model teamwork [Salas et al. 2008]. The two best prospects are related to "shared cognition" and "team training." Here we merely point out the possibilities without implementing them.

Shared Cognition

Shared cognition has been stressed by many researchers to be one of the crucial factors that shape the team performance [Cannon-Bowers and Salas 2001]. To work more efficiently, team members must predict what their teammates are going to do and what they themselves need to do, so that they can select actions consistent and coordinated with those of their teammates [Mathieu et al. 2000]

Shared cognition can form within different kinds of teams. In our context, a natural choice of team is an office. Staff working within an office share a goal, and shared cognition can positively contribute to performance. Different measures have been developed for shared cognition [Cannon-Bowers and Salas 2001]. We can take advantage of these measures to extend our models. Given data, we can use our models to estimate growth in shared cognition.

We put forward one possible measure. Consider an office O with several individuals. We assume team cognition is separable and additive and focus on interpersonal relation in pairs. Define $t(i,j)$ as the length of time that i and j have been working together. We can then use

$$\sum_{i \in O} \left(w_i \sum_{j \in O \setminus \{i\}} t^2(i,j) \right)$$

as a measure of shared cognition. The squaring reflects the increasing speed of forming cognition, and the weight reflects relative importance.

Another possibility is to use network-related concepts. We can define two individuals as connected if their co-working time is larger than a certain threshold. Then we can calculate measures such as the average degree in this network. Similarly, we can attach a weight to each edge based on how long individuals have been working together, and build a weighted graph.

Team Training

Currently, the HR manager does not offer any training to the "team" or "office" as a whole. Like offering training for individuals, we can provide team training. Being trained as a team can improve team members' understanding of each other's roles, promote teamwork, and enhance team performance [Cooke et al. 2004]. We can view team training as an accelerator of team cognition development. So we can multiply the team cognition measure that we developed before by a function of team training to reflect this effect.

Adding this process will not directly affect the dynamic process of staff leaving and the HR manager filling vacancies. However, it will affect the productivity of the company by promoting the efficiency of teamwork. That effect may change the decision-making of HR manager to aim to maximize organizational productivity per unit of cost.

Incorporating Multilayer Networks

We explore recent progress about multilayer networks [Kivelä et al. 2014] and apply this concept to our company to achieve better human resource management.

Our model is based on the organizing structure of the office, and our network describes information flows among all individuals. However, interpersonal relationship is much more complicated. On the one hand, people are consistently entering and leaving the company, causing a change of structure in the network. On the other hand, people have different types of interaction, such as:

- People in the same office work as a team and usually cooperate with each other more frequently.
- People can be close friends with each other regardless of their positions.
- People can have trust in their supervisors, and vice versa.

Since we lack data on such other layers, we can't implement simulations. However, we provide some rules for connecting the information with other layers, as well as some solutions for better churn-rate analysis.

Network based on position

Since the information network is already based on position, other layers can be easily connected by introducing coupling edges. A simple example is the supervision network, which is a tree structure among different positions. Since supervision is a strong relationship, information transmitted through supervision is stronger than in the average information network. Another example is the teammate relationship, where information is transmitted more frequently.

Network based on people

Some relationships—such as friendship and trust—depend not on position but directly on people. Friendship allows for the transmission of more personal information, and trust enables directed transmission of information. Both increase the information intensity, for one tends to accept advice from friends and mentors more often. However, people can switch positions or leave the company, so maintaining a static network is infeasible. One approach, however, is to introduce direct cross-layer links with length zero from a person node to a position node. A qualified HR manager should track the person-position relationship and modify the structure of the network when necessary.

Now let us assume that we have incorporated teammate, friendship, and trust relationship layers into our information network. We provide some improvements over our previous solution to churn-rate analysis and productivity estimation:

- Churn information can now transmit also along other layers of the networks.
- We reduce our time slice from one month to one week, which allows more frequent information transmission between friends and teammates.
- We increase the impact of turnover decisions made by trusted individuals.
- We take friendship into account when calculating shared cognition, where friends in the same office tend to have increased shared cognition, and hence productivity.

Sensitivity Analysis

In this section, we implement sensitivity analysis for our model. Specifically, we test the sensitivity of parameter δ, which we define in calculating productivity. In previous simulations, we had $\delta = 0.1$. Now we test the effect of values $0.05, 0.06, \ldots, 0.15$. **Figure 8** shows the results.

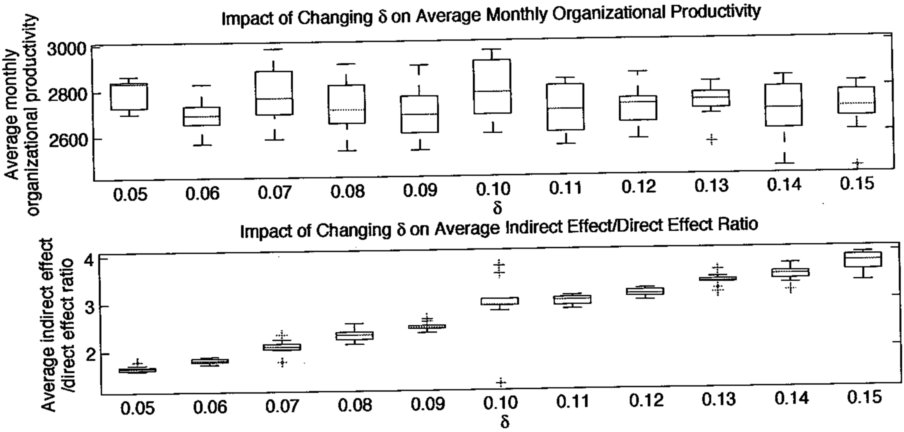

Figure 8. Sensitivity analysis of results of changes in the parameter δ on organizational productivity and on the ratio of indirect effect to direct effect of a resignation.

Productivity is insensitive to δ.

However, the ratio of indirect effect to direct effect of a resignation is sensitive to δ. When δ changes from 0.05 to 0.15, the median value of the ratio changes from less than 2 to nearly 4. However, we have valid reasons for this. Consider how this parameter acts in our model. It is a reflection of the psychological impact intensity for how the dissatisfaction in a job affects a person's productivity. This impact, in reality, can come from shared cognition, the closeness between staff members, company morale and other subtle influences. Much research has been done on tracking these influences [Seligman and Csikszentmihalyi 2000]. So some empirical research may help determine a realistic level of this parameter.

Strengths and Weaknesses

Strengths

- **Simplicity:** Our measures are based on easily-understood principles, and there are simple ways to compute them. In addition, we make minimal assumptions about individual characteristics: Only values for α and β are required for inference.

- **Parameters:** Most of our strategies are nonparametric. The parameters of the churn model have nice properties, allowing for simple parameter estimation, and reducing to a minimum the need for tuning .
- **Coverage:** Our model and measures can simulate various scenarios associated with different churn rates and recruiting and promotion strategies.
- **Flexibility:** Our model can easily incorporate other assumptions. For example, if we assume that an individual accumulates dissatisfaction even without external influence, our model can cover this assumption simply by increasing the β/α ratio in every time period.
- **Appealing simulation results:** Simulation results of our model are very appealing. Not only do they reflect the current situation, but they present insightful predictions for the effect of changes on company situation. We discover that higher churn rates lead to a lower productivity-cost ratio.
- **Heuristics for HR:** HR can gain considerable heuristics from our paper, such as how to change recruiting strategies to sustain a required number of positions, and how to reduce churn rates by providing incentives for those likely to leave.

Weaknesses

- **Simulation volatility**: Although our model has nice statistical properties, results from the simulations show high volatility. One possible remedy is to increase the sampling time, which reduces outcome variance at the cost of computational resources.
- **Unrealistic assumptions**: Some of our measures are based on unrealistic foundations—e.g., the suppositions that productivity increases linearly with training costs, that employees have no inclination towards different positions, etc. The result is imperfect characterization of the problem.
- **Incomplete assumptions**: We fail to consider some other perspectives, such as the positive effects of team cognition on productivity.

Conclusion

We construct a human capital network using the given organizational structure. Building on this network, we devise a model to capture the dynamic process of ICM, including churn, promotion, and recruitment. We simulate the current situation of ICM and get a rather stable churn rate and vacancy rate. The results reproduce well the high churn rate of middle managers and the steadily increasing overall churn rate.

We then define productivity, decompose the effect of churn into direct and indirect effect, and compare their relative sizes. We also calculate the budget that ICM is facing over a long time span. Next, we apply our model to different situations: increase of churn rate and change of promotion strategies. ICM fails to sustain current capacity. Promoting according to likelihood to leave will increase staff by 2.6% and increase productivity by 11.1%, compared with current promotion practice of promoting according to experience.

We explore several potential ways to enrich the model. We discuss the concepts of shared cognition and team training from team science. We apply some concepts related to multilayer network in this context for better depicting the organizational network. We finally evaluate our model by carrying out sensitivity analysis and presenting its strengths and weaknesses. We expect that our model can provide heuristic insights for managing human capital in an organization.

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