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Emergent Research Forum (ERF)

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Abstract

Turnover contagion has created salient challenges for companies and society as turnover itself causes more turnover. Technically, due to the nonlinear growth of overall turnover rate within a short time, turnover is difficult to accurately predict. As a result, predicting and managing turnover contagion have become key issues in people analytics systems. However, existing studies on turnover contagion has primarily focused on its consequence such as time-lagged turnover, while how to identify turnover contagion effect and leverage it to improve the interpretability of turnover prediction algorithm remains under explored. Building upon the behavioral contagion theory, this research-in-progress paper proposes using machine learning method to calculate the turnover contagion effect based on the susceptible-infective epidemic model. This study lays a theoretical foundation to leverage social network data to examine turnover contagion, and practically contributes to managerial practice in designing turnover prediction systems for both efficiency and interpretability.

Keywords

Turnover contagion, contagion effect, social network, behavioral contagion, epidemic model.

Introduction

People analytics system (PAS) has been increasingly applied by top global technology companies (such as Google, IBM, and Baidu), in which building an efficient turnover prediction system is the key to manage and retain talents. *Turnover contagion*, defined as "turnover itself causes more turnover" (Krackhardt & Porter, 1986, p. 50), can create salient problems and challenges on turnover prediction due to three critical features, viz., time variant, cumulative and variating natures from person to person (Teng et al., 2021). According to the Forbes survey (Kelly, 2021), almost 40% of the respondents are considering leaving their employers that year during the time when turnover contagion occurred. During the pandemic and "Great Resignation", turnover contagion has become much more salient (Rickman, 2021).

While turnover contagion has become increasingly problematic in companies, related research is still in its infancy. The extant research on turnover contagion mainly focuses on its consequence (that is, time-lagged turnover) (e.g., Felps et al., 2009; Wang et al., 2016; Chung et al., 2022) rather than identifying its internal mechanism due to the lack of unified and universal methods to measure turnover contagion effect. Existing studies about measuring turnover contagion effect can be divided into three categories, including the survey method (Feeley & Barnett, 1997; Krausz et al., 1999), using time-lagged objective data (Gopalakrishnan et al., 2013; Kumar et al., 2017), and combined these two methods (Kalish, 2019). Although a few studies have considered that turnover contagion may lead to collective turnover and incorporated it into the algorithm

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(e.g., Teng et al., 2021), contagion effect is not yet taken into account as the model input and lack of explicability. To summarize, the extant research (1) leaves a gap for the turnover contagion mechanism and measurement of contagion effect, and (2) lacks design methods to provide the interpretability to predict turnover contagion.

To fill out the above research gaps, the present study focuses on predicting and managing contagion effect in turnover management context. We attempt to answer: *how to identify the turnover contagion effect in enterprise social networks (ESN)?* We follow Porter & Rigby (2020)'s advocation, that is, social network should be used to identify and manage turnover contagion. Building upon behavioral contagion theory (BCT) and the susceptible-infective epidemic model (SIEM) (Newman, 2002), we propose using machine learning method to calculate the turnover contagion effect based on the SIEM. Next, we elucidate more details in this ERF paper by explaining the theoretical background below.

Theoretical Background

Behavioral contagion describes certain undesirable aspects of crowd behavior, most commonly the spread of disorderly, "animal-like" behavior (Le Bon, 1917). The behavioral contagion theory (BCT) was then first introduced by Wheeler (1966) to describe reduced restraints for someone from performing a certain action after another person performs so. Take applause as an example of contagious behavior, people were strongly swayed by other audience members' clapping volume and frequency, or even by just one particularly influential clapper's behavior. Therefore, in analogy to applause, turnover contagion is described as a circumstance in which an employee's coworkers participate in specific behaviors before leaving, and these behaviors occasionally spill over to others, impacting them and increasing their likelihood of resignation (Felps et al., 2009). In other words, when employees notice the turnover-related behavior of colleagues, they use this information to decide whether they should leave their employer. When relating social networks with behavioral contagion and social contagion, observations were made on the exercise contagion in a global social network (Aral & Nicolaides, 2017), the reasons for increased social contagion in a Twitter community (Harrigan et al., 2012), identifying influential and susceptible members of social network (Aral & Walker, 2012). Similarly, on the aspect of turnover contagion, scholars also have done some basic work. For instance, they explored how the turnover process of colleagues affects employees' turnover intention (e.g., Krausz et al., 1999; Felps et al., 2009; Wang et al., 2016; Kalish, 2019), different social network models of employee turnover (Feeley & Barnett, 1997), how leader turnover affects employee turnover intention (e.g., Ballinger et al., 2010; Li et al., 2020).

Turnover contagion is defined as "a process whereby coworkers' turnover-related thoughts, feelings, and/or behaviors spread amongst employees" (Porter & Rigby, 2020), which has the nature of "process", and in this process, many possible antecedents of turnover will be activated including turnover contagion effect (Chung et al., 2022). When concerning the operationalization of turnover contagion effect, prior studies can be summarized into three categories. The first—probably also the largest—school of research adopts the survey method and asks respondents to self-report their turnover intention or actual behavior after their colleagues' resignation (e.g., Feeley & Barnett, 1997; Krausz et al., 1999; Felps et al., 2009). The second school of research uses the objective data to represent the result of turnover contagion (time-lagged turnover) in a certain extent rather than contagious effect (e.g., Gopalakrishnan et al., 2013; Kumar et al., 2017; Chung et al., 2022). The third group of studies employs mixed data including the survey and field data to explore turnover contagion (e.g., Wang et al., 2016; Kalish, 2019), but leaving the intensity and nature of turnover contagion effect not well explained. In summary, existing studies mainly focused on the results of turnover contagion and considered time-lagged turnover (Wang et al., 2016), turnover rate (Li et al., 2020), and turnover intention (Chow et al., 2012) as key variables rather than *contagion effect*, which is the focus of this paper.

In fact, regarding the measurement of contagion effects, the epidemic model first gave a solution (En'ko, 1889), which includes susceptible-infectious (SI), susceptible-infectious-recovered (SIR), susceptible-infectious-recovered-susceptible (SIRS), susceptible-exposed-infectious-recovered (SEIR) four classic models according to different infectious disease. The basic epidemic model investigates transmission speed, spread route, dynamic mechanism, and others to guide the effective prevention and disease control. Among them, the process of turnover contagion can logically correspond to the SI epidemic model (SIEM), which is suitable for the epidemics that only include susceptible and infected people and do not recur. A simple example is HIV infection, infective people contacted with some susceptible people within a certain period of time and pass HIV virus to some susceptible people through blood, sexual, parental and etc. In this study, we map this logic to the turnover contagion. The turnover employee (infective person) has contacted with general employees (susceptible person) in a certain period of time and passed the information, thoughts and emotions of turnover through social communications, meetings, team buildings that can cause the contagion and eventually results in the turnover of other employees. Turnover contagion effect can be seen to essentially represent the possibility that the resigned employees infect the general employees, only after this possibility occurs can it lead to the turnover of other employees. Based on SIEM, this paper conceptualizes and measures the contagion effect of turnover, as detailed below.

Data Description and Research Design

The original dataset is provided by a high-tech company in Asia, which contains all turnover records from 2019 to 2020 (five quarters), along with the ESN data of 1693 employees. All data are anonymized for privacy protection. ESN data mainly includes the communication frequency with time stamp and the IDs of both sides of the communication. In addition, we obtained descriptive profile of each anonymized employee. The descriptive profile dataset mainly includes ID, gender, age, start date, leave date, relative level, etc. To link these two datasets, we integrate ESN data and turnover records in pairs. Each record is a pair of co-workers at any rank over a period of time. Indirect managers and subordinates are also included.

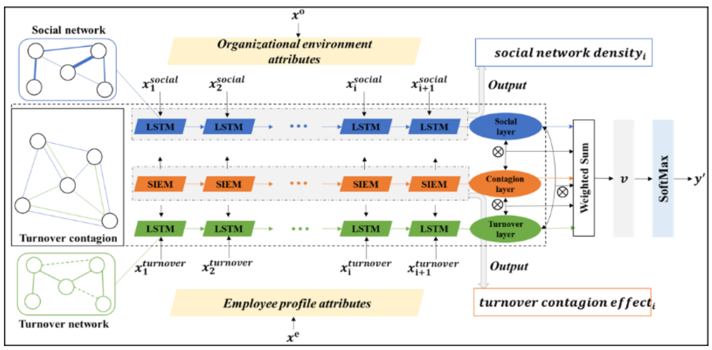

Figure 1 Identifying contagion effect based on LSTM & SIEM

To identify the turnover contagion effect, we designed an algorithm which embedded the susceptible-infectious epidemic model (SIEM) in the sequential neural network model—long short-term memory (LSTM)—to make it more interpretable. A basic single LSTM cell includes an input gate i, a forget gate f and an output gate o, which can be formulated as:

$$f^{(t)} = sigm\left(W_f x^{(t)} + U_f h^{(t-1)} + b_f\right);\ i^{(t)} = sigm\left(W_i x^{(t)} + U_i h^{(t-1)} + b_i\right);$$

$$o^{(t)} = sigm\left(W_o x^{(t)} + U_o h^{(t-1)} + b_o\right);\ u^{(t)} = tanh\left(W_u x^{(t)} + U_u h^{(t-1)} + b_u\right);$$

$$c^{(t)} = i^{(t)} \circ u^{(t)} + f^{(t)} \circ c^{(t-1)};\ h^{(t)} = o^{(t)} \circ \tanh(c^{(t)}).$$

Among them, a memory cell $c^{(t)}$, and a hidden state $h^{(t)}$. $\mathrm{x}^{(t)}$ is the word embedding input at time step t. Operator $\circ$ denotes element-wise multiplication. W, U, and b are the weight vectors of the gate parameters. On this basis, we improve the LSTM by adding a SIEM for contagion effect identification between the forget gate and the input gate, where SIEM can be formulated as $I(t) = \frac{NI_0}{I_0+(N-I_0)e^{-r\beta t}}$. $I(t)$ refers to the number of infected people at time t; N refers to the total number of people; I_0 refers to the initial number of infected people; r refers to the number of susceptible people exposed to the infected person in unit time; β refers to the probability that the susceptible person will get infected after contacting with the susceptible person; t refers to the timestamp. The improved algorithm mechanism and the contagion effect identification process are shown in Figure 1.

Preliminary Analysis

We calculated the contagion effect of turnover in those five quarters by using machine learning method combined with the reverse derivation of the epidemic model. Meanwhile, we conducted the social network analysis to explore the change of turnover contagion and calculate network density. Accordingly, Figure 2 clearly shows the dynamic change of the turnover in social network over time through partial samples, while Figure 3 demonstrates the change of social network density and turnover contagion effect overtime. From T1 to T2, the number of resignations increased sharply, corresponding social network density and contagion effect was greater. T3 has a low turnover contagion effect, and the corresponding number of resignations is also relatively small. This can prove our intuition that the contagion effect of turnover is positively correlated with turnover contagion results (time-lagged turnover).

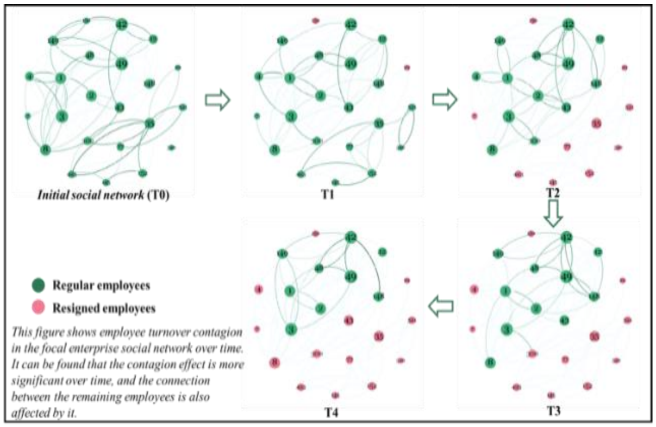

Figure 2 Employee turnover contagion in the ESN

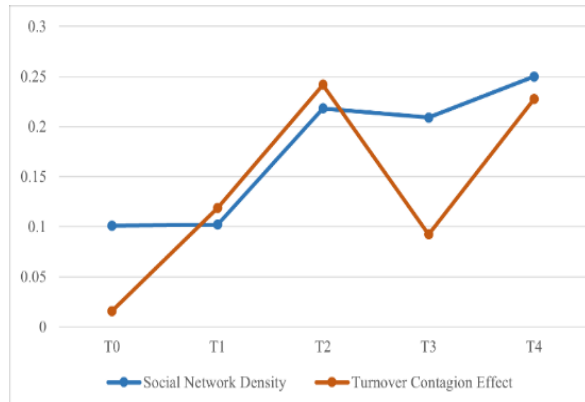

Figure 3 Social network density and turnover contagion effect

Planned Extensions and Expected Contributions

As shown in this ERF paper, turnover contagion effect can be calculated from a new perspective based on LSTM and SIEM. We have meanwhile planned to expand this study as following. First, we obtained the matching data of turnover and social network from 2019 to 2020 for the preliminary analysis. We plan to obtain more dynamic longitudinal data ranging from 2018 to 2021 for future analysis. Based on expanding sample, we will be able to observe more comprehensive changes of turnover contagion to obtain more robust findings. Second, through the dynamic analysis of social turnover networks in this paper, we can preliminarily know that there is an inseparable relationship between the social network characteristics and turnover contagion. Although existing studies have explored the impact of social network on turnover, what role does the contagion effect play in this process is still unclear. Therefore, we plan to further open the black box from social network to turnover and explore the mediating role of contagion effect. Third, this paper does not distinguish the functions of employees, we plan to classify employees (such as leader vs. non-leader, high knowledge diversity vs. low knowledge diversity, etc.) and explore whether the resignation of different types of employees will have different contagious effects. Fourth, we only consider the 0-1 result of whether the employee leaves or not. But in fact, some studies have shown that employees will return to the company that has resigned at a certain rate (Arnold et al., 2020), which is an interesting phenomenon. Then the SIR model could be considered to explore this recovery process of infective employees. In addition, we also expect organizational and national cultures might play a role in turnover contagion and hence in the future researchers can consider applying the proposed models in different organizations and countries for further investigations.

We expect our research contributes to both theory and practice. First, we have extended the turnover contagion theory by identifying the mechanism of turnover contagion and analyzing the role of contagion effect in social networks and turnover. Second, we provide a solid calculation method to measure turnover contagion effect based on the machine learning method and SIEM, which lays a foundation for further Information Systems (IS) research to leverage social network data for examining turnover contagion. Third, we introduce SIEM into LSTM to develop new machine learning algorithms and improve algorithm interpretability, which provides theoretical innovation from the design science perspective. Additionally, this paper provides novel ideas for enterprises to design their turnover prediction systems for both efficiency and interpretability. Moreover, managers can effectively and efficiently identify the next susceptible employee based on the social network data and retain talents by taking interventions, so as to reduce the risk and cost of turnover.

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