Exploiting Connections among Personality, Job Position, and Work Behavior: Evidence from Joint Bayesian Learning

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Personality has been considered as a driving factor for work engagement, which significantly affects people's role performance at work. Although existing research has provided some intuitive understanding of the connection between personality traits and employees' work behaviors, it still lacks effective quantitative tools for modeling personality traits, job position characteristics, and employee work behaviors simultaneously. To this end, in this article, we introduce a data-driven joint Bayesian learning approach, Joint-PJB, to discover explainable joint patterns from massive personality and job-position-related behavioral data. Specifically, Joint-PJB is designed with the knowledgeable guidance of the four-quadrant behavioral model, namely, DISC (Dominance, Influence, Steadiness, Conscientiousness). Based on the real-world data collected from a high-tech company, Joint-PJB aims to highlight personality-job-behavior joint patterns from personality traits, job responsibilities, and work behaviors. The model can measure the matching degree between employees and their work behaviors given their personality and job position characteristics. We find a significant negative correlation between this matching degree and employee turnover intention. Moreover, we also showcase how the identified patterns can be utilized to support real-world talent management decisions. Both case studies and quantitative experiments verify the effectiveness of Joint-PJB for understanding people's personality traits in different job contexts and their impact on work behaviors.

CCS Concepts: • **Information systems → Data mining;**

Additional Key Words and Phrases: Bayesian learning, personality traits, work behavior

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1 INTRODUCTION

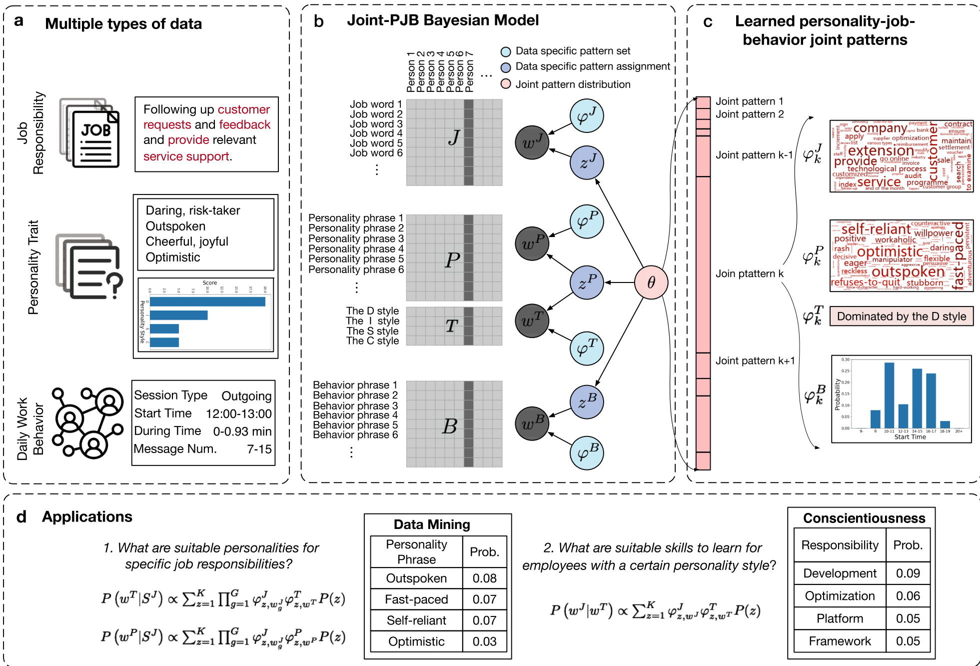
Personality is defined as a set of characteristics of individual-level emotional patterns, which plays an important role in affecting human behaviors, such as economic decisions [18], occupational proficiency [5], language style [32, 61, 75], and social behaviors [6, 52]. Indeed, personality has been considered as a driving factor of work engagement, with a significant impact on enhancing person-job fit within complex organizational contexts. In the literature, researchers in human resource management and psychology have reported extensive evidence showing the connection between personality traits and work behaviors [5, 28, 29], which are usually conducted on limited self-reported questionnaire surveys using classic statistical methods. However, there is still a lack of effective quantitative tools to simultaneously model personality traits, job position characteristics, and the employee's work behaviors. To do so, job-oriented and personality-related behaviors should be jointly explored.

With the rapid development of management information systems and social media applications, an increasing amount of behavioral data can be generated and collected, such as profile information [59], sequential text [20], and user rating activities [25]. Indeed, such data have been widely utilized in recent studies for understanding and predicting people's personalities. However, most of these studies focus on investigating the public social behavioral data for general-purpose tasks, such as digital marketing [11], personalized recommendation [12, 70], and other web services [30, 36]. Few studies have been conducted to explore the alignment of personality traits and work behaviors with job context awareness.

Therefore, we focus on aligning personality traits and job position characteristics in a data-driven quantitative manner, where the potential impact of this alignment on job-oriented behaviors will be explored simultaneously.

Along this line, the primary challenge is to jointly reveal the latent correlations among personality traits, specific jobs, and work behaviors in complex workplace scenarios. Indeed, people's work behaviors are mainly affected by job responsibility, while they can still vary widely due to different personality traits [60, 69]. For example, technical employees with an "outgoing" personality may have much fewer communications than sales, but more contacts than other technical employees with a "reserved" personality.

To this end, in this article, we introduce a data-driven and machine-learning-assisted approach, Joint-PJB, to build a unified Bayesian probabilistic framework for discovering explainable connecting patterns from massive personality, job position, and related behavioral data. Figure 1 shows an overview of the approach. Specifically, Joint-PJB is designed with the knowledgeable guidance of the four-quadrant behavioral model, namely, DISC (Dominance, Influence, Steadiness, Conscientiousness). Based on the real-world data collected from a high-tech company, Joint-PJB aims to jointly model personality traits, job responsibilities, and work behaviors. Also, it discovers the joint patterns hidden in these data, i.e., personality-job-behavior joint patterns. A joint pattern represents some correlated semantic information with job context awareness, aligned in personalities and job responsibilities with the specific work behavior pattern. For example, as shown in Figure 1(c), an employee whose job responsibility is administrative or sale services



Personality Phrase	Prob.
Outspoken	0.08
Fast-paced	0.07
Self-reliant	0.07
Optimistic	0.03

Responsibility	Prob.
Development	0.09
Optimization	0.06
Platform	0.05
Framework	0.05

$$P(w^T|S^J) \propto \sum_{z=1}^{K} \prod_{g=1}^{G} \varphi^J_{z,w^J_g} \varphi^T_{z,w^T} P(z)$$

$$P(w^P|S^J) \propto \sum_{z=1}^{K} \prod_{g=1}^{G} \varphi^J_{z,w^J_g} \varphi^P_{z,w^P} P(z)$$

$$P(w^J|w^T) \propto \sum_{z=1}^{K} \varphi^J_{z,w^J} \varphi^T_{z,w^T} P(z)$$

Fig. 1. An overview of our approach. (a) An example of collected data consisting of job responsibilities, personality traits (including the personality descriptions and corresponding disc scores), and daily work behaviors (including the online communication behaviors formed by a tuple of four attributes). (b) In the proposed Bayesian model, Joint-PJB, where all data can be represented in a matrix manner, the input data instance (gray nodes) is the tuple of columns corresponding to the same person, and other nodes are the learnable latent variables. We assume that there exists a data-specific pattern set for each data type, i.e., φ^J, φ^P, φ^T, and φ^B, respectively. To capture the latent personality-job-behavior joint patterns, we align the data-specific patterns of different data types with strong semantic relations by assuming that multiple types of data of the same person share the same latent joint pattern distribution θ. (c) The learned personality-job-behavior joint patterns, i.e., the connecting tuples among the data-specific pattern sets of multiple data types, where a joint pattern distribution case and a joint pattern case are displayed. Different illustrations are applied for data-specific patterns on different data types. Word clouds are displayed for job words and personality phrases, where the larger the size of each word, the more it is possible that the term occurs. The histogram is applied to illustrate work behaviors. Only the major personality style is shown. (d) Examples of applications enabled by the Joint-PJB model.

(i.e., with keywords "customer", "service", "company", and "provide" in the job description) and the personality is D-style (i.e., with traits "optimistic", "outspoken", and "self-reliant") usually has some typical communication patterns in daily work (i.e., most communications are started between 10:00–11:00 and 14:00–17:00). Based on our model, the matching degree between employees and their work behaviors resulting from their personality and job position characteristics can be measured. We find a significant negative correlation between this matching degree and employee turnover intention, which reveals an important factor for employee engagement and job satisfaction [4, 53]. Furthermore, we also showcase how the identified patterns can be utilized to support real-world talent management decisions. Both case studies and quantitative experiments confirm the effectiveness of our approach to understand people's personality traits in different job contexts and their impacts on work behaviors.

2 RELATED WORK

The related works of this article can generally be grouped into two categories: personality exploration and Bayesian learning for text mining. Last, we will summarize the research gaps.

2.1 Personality Exploration

Personality-related theories have been well developed in psychological research, leading to different types of assessment methods, e.g., the Big Five model [5, 28], the Myers-Briggs Type Indicator (MBTI) [44], and the DISC theory [38]. There exist several differences among their focuses and corresponding applications.

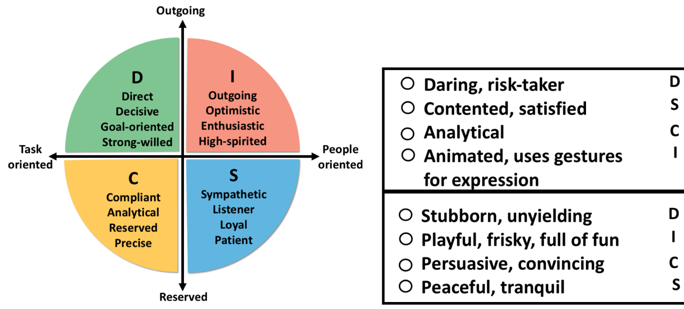
Specifically, the Big Five model aims to assess the identification of individual pathological traits or tendencies and analyze the idealized theoretical types, which may rarely be observed in everyday life [15]. As a result, the Big Five model is most heavily used in academic research and analyzes the potential relationship between personality and individual macro-level behavior outcomes. Concentrating on business management performance, several studies focus on the personalities of executives and managers who play essential roles in organizational outcomes based on Upper Echelons Theory [22, 23]. Researchers analyzed the influence of their Big Five personalities on their strategic and tactical organizational decision-making, which can further impact firm policies and performance [45, 50, 73]. As for the employees, who are the most valuable asset of companies, researchers turned to exploring the correlation between the Big Five personalities with their person–job fitness [17], job satisfaction [26], work attitude [13], turnover intention [78], and even career plan [29]. All those work behaviors are large-scale processes for individuals, which do not appear in work behavior logs. Therefore, most can only be collected by retrospective self-reports with limitations on data scale, data granularity, and experimenter effects.

In contrast, the MBTI and the DISC theory focus more on the normally observed personality aspects. They categorize an individual's personality types by analyzing their approaches to relationships with others [15], or how people feel, behave, and interact with the world around them [58]. In other words, those two personality models tend to describe granular habitual behaviors and reactions that can be observed in everyday life, such as granular communication behaviors used in our article. Both models provide excellent guidance to building and maintaining a solid and effective working team, where the team manager and colleagues can learn corresponding communication skills for dealing with various personality traits for working better together [58]. Therefore, both of them are widely used by business organizations [49] in the service of talent recruitment [48] and management training [43]. In addition, some works also found a significant similarity between the Big Five model with DISC [27] and the MBTI [19], which indicates that those two models may also be useful for analyzing macro-level behaviors.

In this article, we select the DISC theory as the base personality assessment tool to mine the associations between personality traits and granular work behaviors, i.e., daily online communication behaviors. Specifically, the DISC theory centers on four personality styles ("D", "I", "S", and "C"), distinguished by four general orientations, i.e., outgoing, people-oriented, reserved, and task-oriented, respectively, as shown in Figure 2(a). Regarding the assessment procedures, compared with other methods, the DISC questionnaire is easy to administer and interpret and takes less time to complete [1], which is beneficial for collecting adequate feedback reports.

With the rapid growth of internet technologies and social network applications, large-scale behavior data have been collected from different resources, leading to extensive data-driven studies on personality.

Markovikj et al. [37] explored the feasibility of modeling user personality based on the features extracted from Facebook. Wu et al. [71] developed a linear regression model to predict personality based on the Facebook Likes dataset.



(a) The DISC Theory (b) DISC Assessment Questions

Fig. 2. DISC theory and assessment question examples.

Gou et al. [20] developed a lexicon-based approach to predict personality based on the written texts in social media. Wei et al. [68] leveraged the heterogeneous information in social media to achieve a higher performance of personality prediction. Ahmad et al. [2] focused on user-generated texts and developed a deep-learning-based model with natural language processing technologies to extract psychometric dimensions. In addition, although extensive works exist on text processing [16, 63, 74] and work behavior analysis [21, 77], there is little data-driven research focusing on exploring the impact of personality on human behaviors in a work environment.

2.2 Bayesian Learning for Text Mining

Bayesian learning has been explored for text data processing in recent years, such as PLSA [24] and VAE [31, 55], which witnessed great success [14, 33, 65, 66]. Among them, topic models, such as Latent Dirichlet Allocation (LDA) [9] and its variants, have been used in different domains due to high robustness and interpretability, including data-driven talent management studies. For instance, Shen et al. [56, 57] proposed a novel job interview assessment method that can jointly process job responsibilities, résumés, and job interview data assessment to detect shared topics among them. Similar work can be found in [42]. Zhu et al. [77] proposed two dynamic topic models to track the evolution of social emotion in work environments based on Topics over Time (ToT) [67] and Dynamic Topic Model (DTM) [8]. Lin et al. [34] proposed a collaborative topic regression model to profile companies by integrating online public opinions. Also, to integrate additional textual labels for assisting topic modeling, many enhanced topic models were developed, such as the Supervised Topic Model [39], Labeled-LDA [46], Author Topic Model [51] and other extensions [35, 47]. Recently, with the successes of deep neural networks, the use of deep learning on topic models has also attracted more and more attention [76]. For example, GSM [40] can be regarded as the variant of LDA with the variational distributions parameterized by neural networks to approximate the posterior of latent topic distributions. GNTM [54] is a generalization of GSM by representing a document in a graph manner and modeling the non-linear word dependency with graph neural networks. In particular, several works begin to apply the Bayesian learning approaches to talent management in a work environment. In contrast to the existing research, our work focuses on developing a novel topic model to jointly model job responsibility, work behaviors, and personality traits for talent management success.

2.3 Summary of Research Gaps

Significant research gaps are threefold. First, although extensive literature has discussed the connection between personality traits and employees' work behaviors, most focused on the individual macro-level behavior collected by self-reported surveys. There is limited research focusing on granular behaviors stored by work logs on large scales, such as online communication logs. Second, few studies have been conducted to jointly model the connections among personality traits, job position characteristics, and the employee's work behaviors simultaneously. Intuitively, work behaviors are impacted by both job responsibilities and the employee's personality. Therefore, both job-oriented and personality-related behaviors should be explored and distinguished. Last, but not least, related studies mainly focus on theoretical analysis and lack the implementing capacity to benefit specific downstream management applications. For example, the prior work [78] only discussed the correlation between personality and the employee's turnover intention. There is still no way for managers to detect specific employees with intentions to quit because it is not fair to judge based solely on their personality traits. In the following sections, we propose a data-driven and machine-learning-assisted approach to address these gaps.

3 DATA EXPLORATION

This work was conducted on real-world datasets from a high-tech company in China, including personality, job description, and work behavior data. We first conducted a carefully designed questionnaire survey for collecting the personality data based on the extension of the DISC assessment tool, AVA [64], which contains 40 questions. Figure 2(b) shows some question examples. Each survey question asks volunteers to choose one out of four personality-related trait terms, which they believe have the best fit for themselves. The score of each DISC style can be counted by the number of each label chosen by each volunteer. The one with the highest score is considered as the primary personality style. Figure 3(a) shows the distribution of each score of DISC style among the final 1,081 valid samples. We can see that the S style personality scores locate in a higher range than others, which indicates that most people in our samples have *Steadiness* as their primary personality style. We also show the correlation among the scores of DISC styles in Figure 3(b). We can observe strong negative correlations between the D style and the S style as well as the I style and the C style. These findings are consistent with the DISC theory [38, 64]. To further explore the personality traits in a work environment, we collected the job responsibility data and the work behavior data of the volunteers involved in the survey. Specifically, job responsibility includes detailed duties and requirements that may vary for different positions. Also, the work behavior data contain the daily communication attributes exported from an internal Instant Message system. For each conversation session between two employees, we extracted the session's initial time, the message sender and receiver, the session duration, and the total number of messages as attributes. Note that all the data were anonymous and the content of each message was prohibited from being assessed. The distribution of the start time and the number of messages in each session are demonstrated in Figures 3(c) and 3(d), respectively. It can be seen that the majority of sessions appear between 10–11 am and 2–5 pm, whereas they are less likely to occur during lunchtime. Moreover, the curve of the number of messages for each session follows a "long tail" distribution. We also investigate the correlation between the personality of employees and job positions as well as their work behaviors.

Job Positions. Based on the results in Figure 3(e), we find that technology positions, of which the main responsibility includes product development and academic research, generally lead to higher S style scores while having a low score of the I style. In contrast, product positions responsible for product designs result in higher I style scores and the lowest score of the S style. Interestingly, the intern positions also show high I-style scores, indicating that people with internships are more outgoing. They may like to interact more with others to gain work skills and experience quickly. Moreover, in Figure 3(f), we show that the employees at key positions (i.e., employees who have a senior-level job title) usually have higher scores of the D style and lower scores

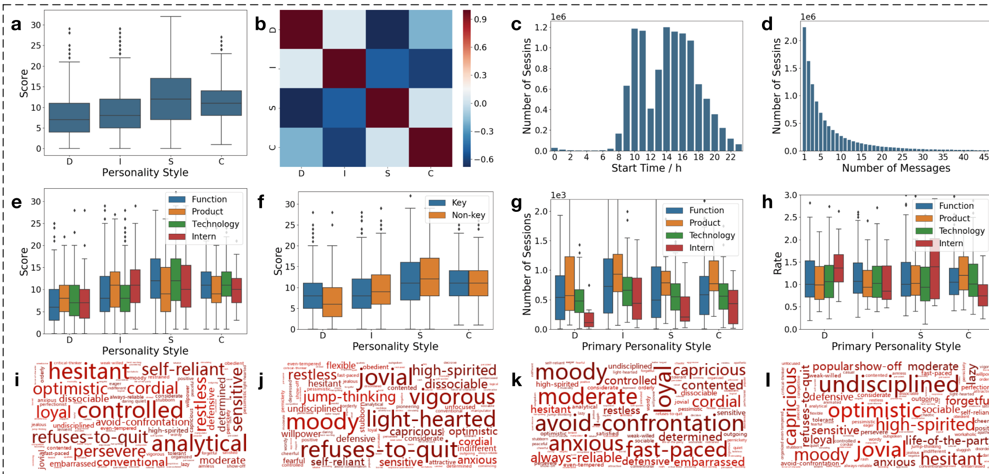


Fig. 3. The preliminary analysis on our real-world datasets. (a) The DISC score distribution. (b) The correlation among DISC scores. (c)(d) The distributions of start time and the number of messages for each work behavior, respectively. (e)(f) The score distribution of DISC styles for different job categories and levels, respectively. (g)(h) The distributions of the number of communication sessions and the rate of outgoing and incoming sessions with respect to different primary DISC styles and work job categories. (i-l) The phrase clouds of personality traits chosen by employee volunteers for different job categories, i.e., (i) technology position, (j) function position, (k) product position, and (l) intern position, where the size of a keyword represents the probability of the occurrence.

of the I style and the S style compared with the non-key employees. More specifically, according to Figures 3(i)–3(l), we observe more keywords such as "analytical", "controlled", and "refuses to quit" in the technology position. In contrast, employees in function positions are more emotional and sensitive, with keywords such as "moody", "capricious", "anxious", and "loyal" to the company. Also, product positions require "jump thinking" to design the novel product with "light-hearted" and "vigorous" traits. Last, interns are often "jovial" and "high-spirited" and have an "optimistic" attitude, sometimes with "undisciplined" traits, however.

Work Behaviors. Based on the analysis in Figures 3(g) and 3(h), we can see that work behaviors significantly vary for different positions. Interesting findings can be summarized as follows. First, people in function and product positions participate in more communication sessions. This finding may be due to the nature of their duties in communicating with clients or developers for ideas and plans. Second, people in technology positions, who have the I style as the primary personality, participate in more communication activities than those with other DISC styles. Third, for product positions, employees who are primarily C style have a higher proportion of incoming than outgoing sessions, which indicates that they are more active in starting a communication. Last, interns have different behavior phrases than other positions. One possible reason is that interns may be assigned to various positions with varying responsibilities.

Based on the preliminary analysis above, we can find some potential connections between personality and work behaviors in different job positions, which are named personality-job-behavior patterns. Note that, in practice, an employee's personality would guide the person's choice of a suitable job position and lead to subsequent behavior at work. However, from a data perspective, specific job responsibilities may also prefer certain personality traits, indicating the mutual relation between those two datasets. Similarly, the employee's work behaviors can also imply the individual's personality and job characteristics. Therefore, inter-correlations exist among those three

Table 1. The Description of Work Behavior Attributes

Attributes	Description
Session Types	Two types: outgoing and incoming.
Start Time	Divided into 8 fragments with 7 split points at 9:00, 10:00, 12:00, 14:00, 17:00,19:00, and 21:00.
Duration Time	Divided into 6 fragments, corresponding the duration time: = 0min, 0–0.93min, 0.93–3.28min, 3.28–8.96min, 8.96–21.92min, and >21.92min.
Number of Messages	Divided into 7 fragments, corresponding to the number of messages = 1, =2, =3, =4, 5–6, 7–15, >16.
A toy example for employee A: (outgoing, 12–13, 0.93–3.28, 7–15).	
Explanatory: employee A started a session with another employee between 12:00 and 14:00, and the duration time of the session is between 0.93–3.28 min and the number of messages is between 7 and 15.	

datasets, although they are not formed in a parallel manner. In the following, we seek effective ways to discover those inter-correlations.

4 EXPLORING PERSONALITY-JOB-BEHAVIOR PATTERNS

Here, we introduce the technical details of our Joint-PJB model for mining interesting personality-job patterns, which can be further used in talent management decisions.

4.1 Problem Statement

Suppose that we have a full employee set M. Based on the data availability, we represent the personality of each employee $m \in M$ as $P_m = \{w^P_{m,p}\}_{p=1}^{N^P_m}$, where $w^P_{m,p}$ is a phrase the m selected during the survey, and N^P_m is the total number of personality phrases selected. In this work, we have $N^P_m = 40, \forall m \in M$, and each phrase $w^P_{m,p}$ is associated with a DISC style $w^T_{m,p} \in V^T = \{D, I, S, or, C\}$. We denote $T_m = \{w^T_{m,p}\}_{p=1}^{N^P_m}$. Similarly, we represent m's job responsibility as $J_m = \{w^J_{m,j}\}_{j=1}^{N^J_m}$, where $w^J_{m,j}$ is a key word (e.g., required skills and duties) on the job description of m, and N^J_m is the total number of the key terms. Furthermore, we extract m's work behavior phrase as $B_m = \{w^B_{m,b}\}_{b=1}^{N^B_m}$, where $w^B_{m,b}$ is defined as a tuple of some attributes of the communication session, such as the start time, duration time, and the number of messages. Table 1 summarizes the attributions involved in our model, with a necessary description and a toy example of the work behavior pattern. We also denote the vocabulary of personality phrases, job responsibilities, and work behaviors as V^P, V^J, and V^B, respectively. Along this line, our goal is to discover the hidden joint patterns among J_m, B_m, and P_m. Specifically, we assume there exist data-specific patterns in different collections. Each data-specific pattern k is formulated as the multinomial distribution parametrized by φ^J_k, φ^B_k, φ^P_k, and φ^T_k on the vocabulary V^J, V^B, V^P, and V^T, respectively. Each collection has individual data-specific pattern sets. We then assume a latent pattern distribution θ_m shared by P_m, J_m, and B_m. Each personality-job-behavior joint pattern k is a tuple of patterns on all collections, i.e., $(\varphi^J_k, \varphi^P_k, \varphi^T_k, \varphi^B_k)$, which indicates that those patterns prefer to appear or occur together under certain job contexts.

4.2 Joint-PJB Bayesian Model

To model the latent correlation in personality, job responsibility, and work behavior, we assume that there exists a latent pattern distribution θ_m, with Dirichlet prior α, shared by J_m, B_m, and P_m for employee m. Different patterns have different multinomial distributions over those three

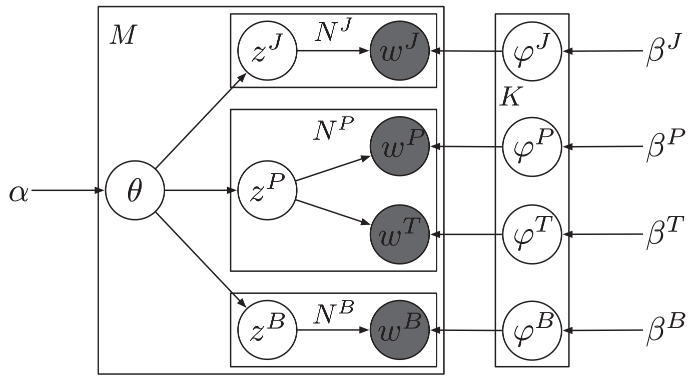


Fig. 4. The graphical representation of the proposed Joint-PJB model.

aspects, i.e., φ^J, φ^B, and φ^P, with respect to $w^J_{m,j}$, $w^B_{m.b}$, and $w^P_{m,p}$, respectively. We also hope to model the specific personality style distribution. Therefore, we follow the ideas in [72] and assume that the corresponding DISC style $w^T_{m,p}$ for each personality trait $w^P_{m,p}$ is generated together from the same pattern assignment $z^P_{m,p} = k$, with multinomial distribution φ^T_k over four DISC styles. The corresponding graphical representation can be found in Figure 4, and the detailed generative process of Joint-PJB is summarized in Algorithm 1.

Here, we use Gibbs sampling to infer the Joint-PJB model. Specifically, we derive the full conditional posteriors and obtain updated rules for the latent assignments and parameters. To update the conditional posterior for the latent pattern of the j-th word $w^J_{m,j} = c$ in the job responsibility of employee m, we have

$$P\left(z^J_{m,j} = z|c, Z^{\neg(J,m,j)}\right) = \frac{N^{\neg(J,m,j)}_{m,z} + \alpha_z}{\sum_{k=1}^{K}(N^{\neg(J,m.j)}_{m,k} + \alpha_k)} \cdot \frac{\mathbb{J}^{\neg(m,j)}_{z,c} + \beta^J_c}{\sum_{t=1}^{|V^J|}(\mathbb{J}^{\neg(m,j)}_{z,t} + \beta^J_t)}, \tag{1}$$

where Z denotes the pattern assignments for all key terms in job responsibility, personality phrases, and work behavior phrases for all employees; $N_{m,k}$ denotes the number of patterns k in all three collections of employee m; and $\mathbb{J}_{k,j}$ denotes the number of key terms j in job responsibility generated by pattern k. V^J denotes the key term set in job responsibility with the size $|V^J|$. Similarly, $\mathbb{B}_{k,b}$ and V^B are defined in behavior phrases; $\mathbb{P}_{k,p}$ and V^P are defined in personality phrases; $\mathbb{T}_{k,p}$ and V^T are defined in personality styles; and the $X^{\neg(*)}$ represents the count of X excluding the component $(*)$, e.g., $Z^{\neg(J,m,j)}$ are the count of Z excluding the j-th key term in the job responsibility of the employee m.

For the latent pattern of work behavior phrases $w^B_{m,b}$ of employee m, the calculation process of the conditional posterior is similar. What should be noted is that the phrase $w^P_{m,p} = s$ in personality traits and corresponding DISC style $w^T_{m,p} = l \in V^T = \{D, I, S, C\}$ should be considered together for sampling their latent pattern:

$$P\left(z^P_{m,p} = z|s, Z^{\neg(P,m,p)}\right) = \frac{N^{\neg(P,m,p)}_{m,z} + \alpha_z}{\sum_{k=1}^{K}(N^{\neg(P,m.p)}_{m,k} + \alpha_k)} \cdot \frac{\mathbb{P}^{\neg(m,p)}_{z,s} + \beta^P_s}{\sum_{t=1}^{|V^P|}(\mathbb{P}^{\neg(m,p)}_{z,t} + \beta^P_t)} \cdot \frac{\mathbb{T}^{\neg(m,p)}_{z,l} + \beta^T_l}{\sum_{t=1}^{|V^T|}(\mathbb{T}^{\neg(m,p)}_{z,t} + \beta^T_t)}. \tag{2}$$

After the iterations, all latent assignments can be learned, and we can estimate all model parameters $\varphi^J_{z,w}$, $\varphi^B_{z,w}$, $\varphi^P_{z,w}$, $\varphi^T_{z,w}$ $\theta_{m,z}$, as in the similar approach of LDA [9].

ALGORITHM 1: The Generative Process of Joint-PJB

1. For each pattern $k = 1, \ldots, K$:
   (a) Draw φ_k^J,φ_k^B, φ_k^P, and φ_k^T from the Dirichlet prior $Dir(\beta^J)$, $Dir(\beta^B)$, $Dir(\beta^P)$, and $Dir(\beta^T)$, respectively.
2. For each employee m:
   (a) Draw pattern distribution θ_m from the Dirichlet prior $Dir(\alpha)$
   (b) For each key term $w_{m,p}^J$ in job responsibility:
      - Draw pattern assignment $z_{m,j}^J \sim Mulit(\theta_m)$
      - Draw key term $w_{m,p}^J \sim Mulit(\varphi_{z_{m,p}^J}^J)$
   (c) For each work behavior phrase $w_{m,b}^B$:
      - Draw pattern assignment $z_{m,b}^B \sim Mulit(\theta_m)$
      - Draw phrase $w_{m,b}^B \sim Mulit(\varphi_{z_{m,b}^B}^B)$
   (d) For each phrase $w_{m,p}^P$ and its DISC style $w_{m,p}^T$ in the characteristic set of personality:
      - Draw pattern assignment $z_{m,p}^P \sim Mulit(\theta_m)$
      - Draw phrase $w_{m,p}^P \sim Mulit(\varphi_{z_{m,p}^P}^P)$
      - Draw the DISC style $w_{m,p}^T \sim Mulit(\varphi_{z_{m,p}^P}^T)$

4.3 Personality-Job-Behavior Joint Patterns

Here, we validate Joint-PJB on exploring personality-job-behavior joint patterns. First, to measure the quality of the learned patterns quantitatively, we follow previous topic models [9] and use Normalized Pointwise Mutual Information (NPMI) as the metric to measure the interpretability of a pattern by computing the semantic coherence in the most significant words [41]. A higher value indicates better quality. Specifically, NPMI is computed on the top items of each pattern with the original corpus of each collection as the reference documents, i.e.,

$$NPMI = \frac{1}{K} \sum_{k=1}^{K} \sum_{i,j=1}^{10} \frac{\log \frac{P(s_i^{(k)}, s_j^{(k)})}{P(s_i^{(k)})P(s_j^{(k)})}}{-\log P(s_i^{(k)}, s_j^{(k)})}, \tag{3}$$

where $\{s_1^{(k)}, \ldots, s_{10}^{(k)}\}$ denotes the top-10 most likely items in pattern k of different collections, such as the personality phrases, behavior phrases, or job-related words. $P(s_i^{(k)}, s_j^{(k)})$ represents the possibility of item $s_i^{(k)}$ and $s_j^{(k)}$ co-occurring in an instance, and $P(s_i^{(k)})$ is the corresponding marginal possibility. Both are approximate values with empirical counts.

In addition, we introduce two advanced baselines for comparisons: **LDA** [9], the most classic topic model, and **GSM** [40], a state-of-the-art topic model by parameterizing variational distribution with neural networks. In particular, to jointly model personality, job, and work behaviors, we merge the employee's personality phrases, job responsibilities, and work behavior phrases as one instance for training LDA and GSM. As a result, the topic-specific distribution is supported by the combination of vocabulary V^P, V^J, and V^B. We can split each topic into three distributions by separating this support into three vocabularies. Along this line, we can compute the NPMI metric on each collection respectively. Note that, due to the small size of vocabulary V^T, i.e., 4, it is less significant to evaluate the quality of patterns ϕ^T. However, using DISC styles can contribute to the overall qualities of other patterns. To confirm this, we also introduce a variant of Joint-PJB,

Table 2. The NPMI Scores of Different Models with Varying Numbers of Patterns and Topics

Number of Topics		10	20	30	50	70	100
Job	LDA	−0.1294	−0.1611	−0.1864	−0.1816	−0.1548	−0.1828
	GSM	−0.0210	−0.0007	**−0.0173**	**−0.0038**	−0.0283	−0.0197
	Joint-pJB	0.0033	−0.0212	−0.0307	−0.0077	**-0.0521**	−0.1338
	Joint-PJB	**0.0093**	**0.0002**	−0.0203	−0.0438	−0.0575	**−0.1046**
Behavior	LDA	−0.2522	−0.2125	−0.2171	−0.2072	−0.2192	−0.2201
	GSM	−0.2430	−0.1903	−0.1628	−0.1775	−0.1681	−0.1790
	Joint-pJB	−0.0979	−0.0604	−0.1006	**−0.1047**	**−0.1107**	−0.1589
	Joint-PJB	**0.0070**	**−0.0320**	**−0.0751**	−0.1171	−0.1357	**−0.1567**
Personality	LDA	−0.2233	−0.2157	−0.2154	−0.2289	−0.2104	**−0.1767**
	GSM	−0.2419	−0.2160	−0.2100	−0.1970	−0.2091	−0.2142
	Joint-pJB	−0.2043	−0.1981	−0.1995	−0.2070	−0.2128	−0.2163
	Joint-PJB	**−0.1708**	**−0.1724**	**−0.1766**	**−0.1955**	**−0.2063**	−0.2118

The best and second scores are highlighted in boldface and with an underline, respectively.

Joint-pJB ('p' for personality **p**hrase), as a baseline, where the DISC style information is removed and only the personality phrases are preserved to represent employee personality. We trained the Joint-PJB and other models on the full dataset. To ensure effectiveness and avoid missing values, we removed the stop-words in the job responsibility. We also filtered out employees with the word number of job responsibilities less than 20. During the training process, we empirically set fixed parameters $\{\alpha, \beta^J, \beta^B, \beta^P, \beta^T\} = \{0.1, 0.01, 0.01, 0.01, 0.01\}$, and set the maximal iteration times to 1000 in Joint-PJB and Joint-pJB. As for LDA and GSM, we followed the original papers to set up parameters or neural networks.

Table 2 summarizes the NPMI scores of different models on job responsibility, work behaviors, and personality phrases with varying numbers of patterns or topics. We find that Joint-PJB achieves the best performance on most of the settings. Meanwhile, GSM, compared with LDA, is a competitive baseline, especially for job responsibility, which may be attributed to the powerful expressivity of neural networks. In addition, comparing Joint-PJB and Joint-pJB, we derive that using DISC styles in our Joint-PJB model can boost the quality of the learned patterns. Last, comparing the performance with different numbers of patterns, we find that Joint-PJB achieves the highest NPMI score, with ten patterns on all three collections. Therefore, we fix the number of patterns in Joint-PJB as 10 in the following experiment.

Then, to provide an illustrative understanding of the learned personality-job-behavior patterns, Figure 5 summarizes the detailed information of four out of ten latent patterns learned by our Joint-PJB. We find that both Joint Pattern 6 and Joint Pattern 7 have a certain level of similarity, and the same for Joint Pattern 3 and Joint Pattern 8.

Joint Pattern 6 & Joint Pattern 7. First, the word cloud of job responsibility shows that the two learned joint patterns fall into the "function" position category mainly responsible for administrative or sale services. We can observe many keywords in large sizes, such as "customer", "service", "company", "provide", and "assist", where the size of a keyword represents the probability of appearing in the pattern. Along this line, we can also identify the similarity of the work behaviors in the following ways. First, for the employees identified in the two joint patterns, the occurrence probability of outgoing sessions is consistently higher than the incoming sessions. Second, more communication sessions happen in the normal working time (i.e., 9 am–11 am and 2 pm–5 pm). Third, there is nearly zero conversation after 6 pm. However, an interesting finding is that the corresponding personalities of the two patterns are quite different. People's personality in Joint Pattern 6

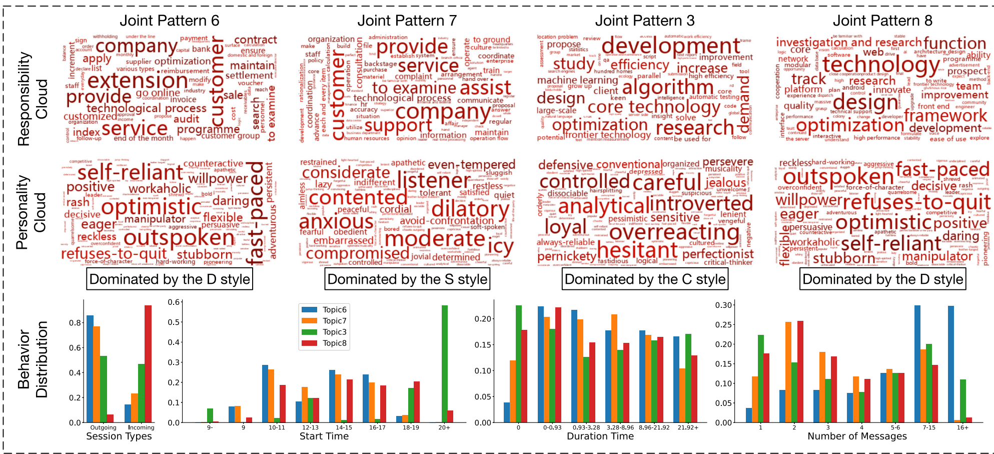


Fig. 5. Some examples of the explored personality-job-behavior joint patterns. For each pattern, we show the key term cloud of the job responsibility in the first line, the phrase cloud of personality traits with the corresponding dominant DISC style in the second line, and the distribution of work behavior attributes in the last line. In particular, the behavior attributes include the communication session type (i.e., incoming or outgoing), session start time, session duration, and the number of messages. For example, we denote the session type by S_b, given the b-th work behavior phrase. Then, the probability that the session type S is outgoing (O) for the joint pattern z can be computed as $\sum_{b=1}^{|V^B|} \varphi_{z,b}^{B} \mathbb{I}[S_b, O]$, where the function $\mathbb{I}[x, y] = 1$, only if $x = y$; otherwise, $\mathbb{I}[x, y] = 0$.

is dominated by the D style personality represented by keywords such as "fast-paced", "self-reliant", "willpower", "outspoken", and "daring". In contrast, the primary personality of people in Joint Pattern 7 is dominated by the S-style personality represented by keywords such as "listener", "moderate", and "considerate". Following that, we identify some differences regarding the work behaviors in the two joint patterns. For instance, the number of messages in each session is generally larger in Joint Pattern 6. Also, the communication sessions usually end longer in Joint Pattern 6.

Joint Pattern 3 & Joint Pattern 8. We find that the job responsibility discovered in these two joint patterns are closely related to the "technical" position category, which is mainly responsible for the development and research jobs. We see many frequently appearing keywords such as "development", "technology", "algorithm", and "optimization". Regarding the work behaviors, for Joint Pattern 3 and Joint Pattern 8, more sessions are occurring after 6 pm compared with Joint Pattern 6 and Joint Pattern 7, and higher percentages of short communication sessions. Meanwhile, small amounts of messages per session with short session durations are found. Furthermore, for Joint Pattern 3, if considering people with the C style personality, their communication activities usually occur at night after 9 pm. For Joint Pattern 8, with the D-style personality, most communication sessions start with an incoming message.

5 DECISION SUPPORT FOR TALENT MANAGEMENT

Here, we further showcase the capacity of our Joint-PJB model in supporting the decision-making process in two functional areas of talent management: Talent Recruitment and Talent Retention, which aim to hire suitable candidates and retain excellent employees.

5.1 Supports for Talent Recruitment

Based on the personality-job-behavior joint patterns, we study two important problems in talent management: (1) "*What are the suitable personalities for specific job responsibilities?*" and (2) "*What* *are the suitable skills to learn for employees with a certain personality style?*". Due to the probabilistic definition of Joint-PJB, we can connect the probabilities of personality traits, personality phrases, and keywords in the job description with the Bayes formula.

Formally, given a set of key terms $S^J = \{w_g^J\}_{g=1}^G \in V^J$ regarding job responsibilities, we estimate the fitness of each DISC style personality $l \in V^T$ based on mined personality-job-behavior joint patterns via

$$P(w^T|S^J) = \sum_{z=1}^{K} P(w^T|z)p(z|S^J) \propto \sum_{z=1}^{K}\prod_{g=1}^{G} \varphi^J_{z,w_g^J}\varphi^T_{z,w^T}P(z), \tag{4}$$

where $P(z)$ can be computed by $\frac{\sum_{m=1}^{M} N_{m,z}}{\sum_{m=1,k=1}^{M,K} N_{m,k}}$ after training model. Similarly, we can estimate the goodness-of-fit of the exact personality phrase $w^P \in V^P$ via

$$P(w^P|S^J) = \sum_{z=1}^{K} P(w^P|z)p(z|S^J) \propto \sum_{z=1}^{K}\prod_{g=1}^{G} \varphi^J_{z,w_g^J}\varphi^P_{z,w^P}P(z). \tag{5}$$

In turn, given the DISC style trait $w^T \in V^T$, we can rank key terms $w^J \in V^J$ in job responsibility to reveal the right skills or responsibilities via

$$P(w^J|w^T) = \sum_{z=1}^{K} P(z|w^T)p(w^J|z) \propto \sum_{z=1}^{K} \varphi^J_{z,w^J}\varphi^T_{z,w^T}P(z). \tag{6}$$

Figure 6 shows some case studies. For the first question, supposing we have a list of key terms about some jobs, we can generate a corresponding ranking of personality traits and DISC styles. For example, given the job responsibility keywords "data mining, and data analysis", the D style (i.e., dominance) personality is the most favorable one among the four styles, and related personality traits are presented in the personality cloud. We believe that the results are reasonable. The key term "data mining" is often associated with the development and research positions, which require personality traits such as "outspoken" and "speaking freely and boldly" to express their idea and "fast-paced" to explore new research areas. Furthermore, relevant positions require characters such as "confident" attitude and "willpower" to suffer the pressures from the possibility of failure with project deadlines. Following the same method, we can see that the positions responsible for "code development and deployment" prefer the C style (conscientiousness) personality, who are generally "analytical" and "careful" and do things "orderly". Hiring people with such personality traits will reduce mistakes and delay in project development. Our results also show that employees with the I style should be hired for positions related to "product research, analysis and design" and "product sales and promotion". They are usually "light-hearted", "high-spirited", "jovial" and "popular" in their social connections, allowing them to handle communication jobs easily. In addition, positions such as "product sales" may also need the employees to be "loyal" to the company, which indicates that the C style personality is also essential. Positions doing "product design" also require people to be "self-reliant" and "outspoken", which leads to D-style candidates' preference.

For the second question, we can find that the "innovative" skills, such as "machine learning", "large-scale" data processing, and "data mining", are suitable to be learned by people with the D style (dominance) personality. The suitable responsibilities for the I style (i.e., influence) employee contain keywords such as "recruit", "demand", and "feedback", which may lead to positions that require more communication skills. For people who are S style (i.e., steadiness) or C style (i.e., conscientiousness), jobs related to technology are more suitable. Skills such as "algorithm", "development", "on-line" and "optimization" are highly demanded. However, compared with the S style,

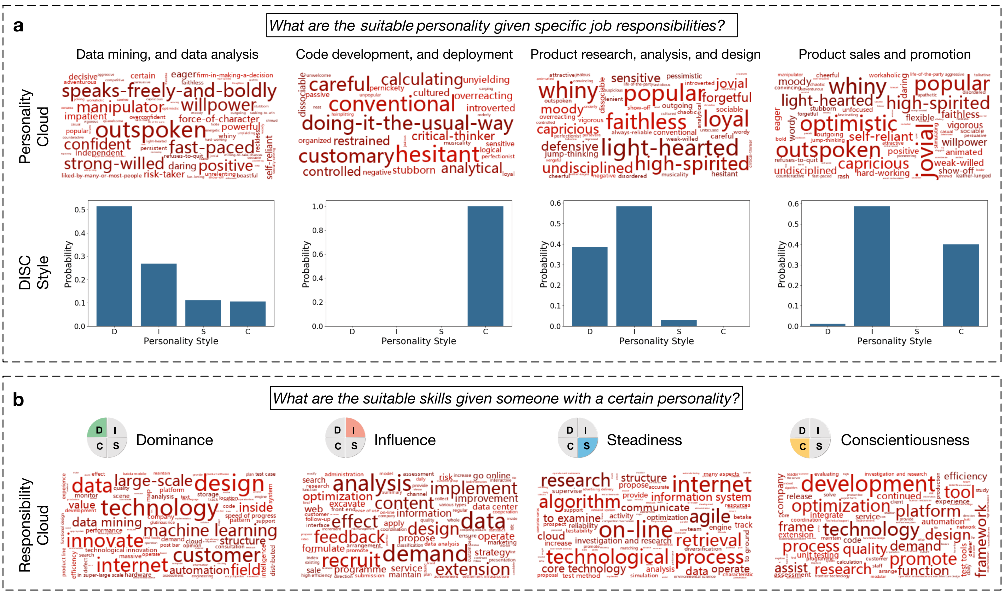


Fig. 6. Case studies of applications for recruitment tasks. (a) The solutions for the question "*What are the suitable personalities for specific job responsibilities?*". Given a list of key terms about some jobs in the first line, the corresponding ranking of personality traits and DISC styles are displayed in the following two lines. (b) The solutions for the question "*What are the suitable skills to learn for employees with a certain personality style?*". Given the specific DISC style in the first line, the suitable job responsibilities lie in the last line.

employees with a C style personality are more suitable for some positions about foundational development with keywords such as "platform", "tool", and "framework" or some service work with keyword "assist", such as product "promotion".

5.2 Supports for Talent Retention

Talent retention aims to retain valuable talents, where an essential process is to identify turnover intention hidden in work behaviors with effective measurements. Along this line, it should be essential to detect abnormal work-related behavior considering individual personality traits. Therefore, we propose to measure the matching degree between employees and work behaviors with the explored personality-job-behavior joint patterns.

Formally, for each employee, given the tuple $\{J_g, P_g\}$ of job responsibility and personality for the employee g and the work behavior B_g, we first infer the joint pattern distribution θ_g^{JP} of $\{J_g, P_g\}$ and the pattern distribution θ_g^B of B_g as their representation vectors, respectively. Then, the matching degree f_g of $\{J_g, P_g\}$ and B_g can be measured by the similarity between θ_g^{JP} and θ_g^B, such as cosine similarity or KL divergence, i.e.,

$$\begin{aligned} f_g^{cos} &= \frac{\theta_g^B \cdot \theta_g^{JP}}{||\theta_g^B||_2 ||\theta_g^{JP}||_2}, \\ f_g^{KL} &= -\frac{1}{2}\sum_{k=1}^{K}\left(\theta_{g,k}^B \log\frac{\theta_{g,k}^B}{\theta_{g,k}^{JP}} + \theta_{g,k}^{JP}\log\frac{\theta_{g,k}^{JP}}{\theta_{g,k}^B}\right), \end{aligned} \tag{7}$$

where $\cdot$ is the dot product and $|| * ||_2$ is the 2-norm operation.

To better comparisons, we involve three advanced baselines and their variants. Specifically, besides **LDA** and **GSM** mentioned above, we further introduce **VAE** [31] as another baseline, which is a state-of-the-art Bayesian-based neural network model with a Gaussian random variable as the representation of the input instance. Similarly, we merge the employee's personality phrases P_g, job responsibility J_g, and work behavior phrases B_g into one instance as the input data. The KL divergence is computed on the Gaussian random variables of $\{J_g, P_g\}$ and B_g, while the cosine similarity is based on their expectations. To evaluate the importance of personality traits, we also removed features related to personalities and obtained additional baselines, **LDA-P**, **GSM-P**, and **VAE-P**. In addition, to evaluate the effectiveness of different components in Joint-PJB, we also constructed several variants of our approaches as additional baselines. Specifically, besides **Joint-pJB** mentioned above, we further designed three variants: **Joint-JB**, where personality-related features, including both personality phrases and DISC styles, are removed from the input; **Joint-PB**, where job responsibilities are removed from the input; **Joint-sJB**, where the personality phrases are removed from the input, and only DISC styles are preserved to represent the employee's personality.

The quantitative experimental results are summarized in Table 3. In particular, we regarded this experiment as a classification task, where the pair $(\{J_i, P_i\}, B_i)$ for each person i in our dataset is regarded as a positive sample, and negative samples are constructed by randomly selecting another work behavior set $B_{i'}$ for each person i. The evaluation metrics include the precision-recall AUC (PR_AUC) and the receiver operating characteristic AUC (ROC_AUC), which are both classical classification metrics [62]. As expected, our method consistently outperforms all baselines given the limitation of LDA, GSM, and VAE in capturing shared patterns among a job, personality, and work behavior. Also, the results confirm the importance of personality in the job-behavior fit task by comparing LDA, GSM, and VAE with their variants, or Joint-PJB with Joint-JB. In addition, comparing Joint-PJB with its variants, we find that each component involved in Joint-PJB benefits the overall performance. In particular, the most competitive variant is Joint-pJB, where personality phrases contain more information than DISC styles. Meanwhile, comparing different baselines, we can observe that GSM performs better than LDA, which may contribute to the expressivity of neural networks. VAE performs better than the other two baselines, especially regarding Cosine similarity. It may be due to the flexibility of Gaussian random variables compared with the topic proportions in LDA and GSM, where the value on each dimension is constrained to be positive and less than 1. However, VAE fails to provide intuitive interpretability like topic models and our models, which is essential in personality analysis.

We have also investigated the relationship between the matching degree of $\{J_g, P_g\}$ and B_g with the turnover intention of employees. Indeed, it has been reported that the degree of person–job fit usually has a significant impact on employee engagement and further influences their turnover intention [3, 7, 10]. In our dataset, among the 471 employees in technology positions, 83 of them resigned within one year after the survey. As shown in Table 4, by using a typical two-sample student's t-test, we find that Joint-PJB can distinguish those two employee groups with a significant margin on the matching degrees in terms of both Cosine similarity and KL divergence, which indicates a negative correlation between this matching degree and employee's turnover intention. Joint-pJB and Joint-sJB can also differentiate resigned employees and others regarding KL divergence.

However, the baselines, i.e., LDA, GSM, VAE, and their variant, cannot distinguish those two employee groups.

6 CONCLUSION AND FUTURE WORKS

In this article, we developed a data-driven joint Bayesian learning approach, Joint-PJB, for discovering explainable joint patterns from massive personality and job-position-related behavioral

Table 3. The Results of Measuring the Matching Degree Between Employees and Work Behaviors

	Cosine Similarity		KL Divergence	
	PR_AUC	ROC_AUC	PR_AUC	ROC_AUC
LDA-P	0.6835	0.7226	0.6323	0.6587
LDA	0.7371	0.7786	0.7244	0.7719
VAE-P	0.8107	0.8296	0.7148	0.7886
VAE	0.8214	0.8332	0.7044	0.7919
GSM-P	0.7028	0.7297	0.6693	0.7291
GSM	0.7707	0.8110	0.7206	0.7958
Joint-JB	0.8384	0.8534	0.8117	0.8281
Joint-PB	0.8255	0.8202	0.7935	0.7841
Joint-pJB	0.8495	<u>0.8599</u>	<u>0.8376</u>	<u>0.8431</u>
Joint-sJB	<u>0.8529</u>	0.8444	0.8296	0.8183
Joint-PJB	**0.8568**	**0.8629**	**0.8630**	**0.8571**

The best and second scores are highlighted in boldface and with an underline, respectively.

Table 4. The Two-Sample Student's T-test on the Matching Degree of Employees and Work Behaviors

	avg. of f^{cos}			avg. of f^{kl}		
	resigned employees	others	p-value	resigned employees	others	p-value
LDA-P	0.0179	0.0069	0.1371	−9.8603	−0.1596	0.1396
LDA	0.0030	0.0026	0.7675	−9.6519	−9.7422	0.5258
VAE-P	0.0600	0.0877	0.2444	−60.2365	−55.9212	0.3006
VAE	−0.0693	−0.0970	0.0845	−221.8049	−215.7678	0.6819
GSM-P	0.2312	0.2860	0.1957	−3.2268	−3.0979	0.5833
GSM	0.0927	0.0782	0.1980	−3.2298	−3.2719	0.6902
Joint-JB	0.5092	0.5180	0.7935	−2.1363	−2.3215	0.2164
Joint-PB	0.4340	0.4580	0.3067	−1.6813	−1.5503	0.0753
Joint-pJB	0.4480	0.4777	0.2120	−1.658	−1.5080	**0.0183**
Joint-sJB	0.4701	0.4951	0.2799	−1.3420	−1.2365	**0.0380**
Joint-PJB	0.5968	0.6439	**0.0328**	−1.0265	−0.8950	**0.0345**

A two-sample student's t-test (two-tailed) has been conducted on two employee groups, i.e., employees resigned in one year after our survey and others. The averages of score f^{cos} and f^{kl} in both groups have been reported with the confidence level p-value in the t-test. We believe that the scores in the two groups are different significantly when p-value < 0.05.

data. Based on the real-world data collected from a high-tech company, Joint-PJB can highlight personality-job-behavior joint patterns from personality traits, job descriptions, and work behaviors. In particular, based on this model, the matching degree between employees and their work behaviors that resulted can be measured from their personality and job position characteristics. We have also found a significant negative correlation between this matching degree and employee turnover intention. Moreover, we have showcased how the identified patterns can be utilized to support real-world talent management decisions. Both case studies and quantitative experiments have clearly validated the effectiveness of Joint-PJB for understanding people's personality traits in different job contexts and their impact on work behaviors.

This article also focuses on the connection between personality, job responsibilities, and work behaviors. Indeed, there exist other features that may affect work behaviors, such as gender and age. It is an interesting direction for future work to explore the more detailed connections among these factors, while it also requires more personality-related data. We have noted that the neural network-based models achieve competitive performance in our experiments, such as GSM. Therefore, another research direction is to boost the performance of our model by developing more advanced neural network models.

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