Research Article

Emotion Monitoring of Hotel Staff Based on Mobile Network and Resource Allocation Algorithm

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With the continuous growth of the number of mobile devices and the continuous development of the mobile internet, people’s demand for mobile communication services is also increasing. However, the wireless spectrum resources of cellular mobile communication networks are limited and are becoming increasingly scarce and tense. In order to improve the utilization of wireless spectrum resources, people have proposed the concept of device-to-device communication. In order to improve the robustness of the system and transmission delay tolerance service, which allows users to interrupt the probability method has certain tolerance, the maximum transmission power is greater than that of the traditional robust algorithm. By monitoring the emotions of hotel employees, it can be seen that the performance accuracy of the robust algorithm in this paper is high. Low job burnout will have a negative impact on hurt job satisfaction, while emotional fatigue and depersonalization will not directly affect job satisfaction. Among the two outcome variables of job burnout and job satisfaction, surface behavior positively affects emotional exhaustion and depersonalization but has no significant effect on job satisfaction. Deep behavior negatively affects depersonalization and low sense of accomplishment and positively affects work satisfaction.

1. Introduction

With the gradual maturity of the domestic hotel industry market, the focus of competition in the industry has changed from providing high-configuration hardware facilities to providing high-level customer service [1]. This means that the emotional expression of the hotel staff will affect the quality of service customers feel, as well as customer satisfaction [2]. Customer assets are important intangible assets of hotels. Therefore, the emotional management of hotel employees has always been the focus of hotel managers [3]. Among them, job burnout caused a lot of discussions. In addition to physical and mental work, hotel employees in a high-contact service industry, regardless of their emotional state, need to perform a large number of emotional displays required by the organization, which can lead to job burnout, affect job satisfaction and job performance, and even resign tendency [4]. A large number of other outcome variables can also be mediated or partially mediated through job burnout. Currently, relevant research focuses on emotional labor strategies [5]. Another aspect of emotional labor that belongs to the category of emotional labor is that emotional labor pays less attention, and the results of related research on emotional labor strategies often appear contradictory. Therefore, an in-depth and systematic study of emotional labor and job burnout can help clarify the mechanism of emotional labor and is a useful exploration for deepening the existing framework [6].

2. Related Work

Emotional labor has two meanings: one is the requirement of emotional labor and the other is the strategy of emotional labor. This research divides emotional work into emotional labor strategy and emotional labor demand [7]. From the perspective of labeling rules and interactive expectations, labeling rules and interactive expectations integrate the relevant content of emotional labor needs. When it comes to emotional labor, the literature integrates the two viewpoints of display rules and interaction expectations [8]. It analyzes
the role of identity theory on individuals, connects emotional labor requirements with emotional labor strategies, and proposes that identity can be used as an intermediary mechanism for the relationship between parameters. The importance of emotional management is recognized. The literature proposes that people believe that emotional labor includes the workload of emotional labor, and other aspects of emotional labor that belong to the category of emotional labor is emotional labor [9]. Therefore, in-depth and systematic research on emotional labor and job burnout can help clarify the mechanism of emotional labor and have a direct impact on job burnout syndrome. The literature pointed out that emotional labor demand has a positive impact on job burnout syndrome, and other dimensions have received less attention [10]. Relevant research results on emotional labor strategies often appear contradictory. Therefore, an in-depth and systematic study of emotional labor and job burnout can help clarify the mechanism of emotional labor and is a useful exploration for deepening the existing framework [11]. We are discussing the impact of emotional labor on job burnout, and emotional labor requirements have a positive effect on job burnout [12]. Both deep acting and superficial acting play a complete mediating role in emotional labor demand and job burnout. The direct impact of emotional labor demand on job burnout is only in natural regulation, but it inhibits the second half of the coordination path. The literature proposes to integrate emotional labor demand into the emotional labor framework [13]. Finally, five dimensions of emotional labor demand, emotional labor routine, emotional expression diversity, positive emotional display rules, and negative emotional display rules are determined [14]. This division method will meet the organizational regulations of emotional labor and the actual needs of employees in emotional labor. The needs are divided in a unified way, which actively regulates the relationship between the employees’ emotional work needs and the employees’ superficial and deep roles [15, 16]. This is the basis for the dimensional division of emotional labor needs in this study.

3. D2D Network-Based Dynamic Quota Resource Allocation Algorithm Design

3.1. System Model. As shown in Figure 1, this article uses a multiuser mat cognitive D2D communication system in a spectrum sharing model. This system has n cellular base stations, m cellular ND2 users, and the user sets are defined as \( M \) and \( N \), respectively. The spectrum resource of the cellular system is divided into multiple subchannels, and each cellular user uses an orthogonal subchannel for uplink data transmission, thus avoiding the influence of the same-layer interference between cellular users. Assuming that each pair of the D2D users has spectrum awareness capabilities, flexibly implements mode selection, and resource scheduling, since it is based on the underlying spectrum sharing mode, D2D users need to control their interference power to not to exceed a certain level when multiplexing cellular user frequency and it is assumed that all wireless channels obey this distribution.

Considering the interference of cellular users to D2D users and the interference of other D2D users to the current D2D users, the signal-to-interference-to-noise ratio of the nth D2D user receiver is as the following formula:

\[
\gamma_n = \frac{p_c^m h_{c,n}^m}{p_c^m h_{c,n}^m + \sum_{i=1,i\neq n}^N p_i^m h_{i,n}^m + N_0}.
\]
Therefore, the total rate of all D2D users can be described as the following formula:

\[
R = \sum_{n=1}^{N} \sum_{m=1}^{N} \log_2 (1 + \gamma_n^m). 
\]

(2)

Define the circuit power consumption of each pair of D2D users as \( PC \), and then the total power consumption of D2D users is as the following formula:

\[
E = \sum_{n=1}^{N} \sum_{m=1}^{N} P_n^m + NPC.
\]

(3)

Further considering the need to protect the communication quality of each cellular user, there are the following interference power constraints:

\[
\sum_{n=1}^{N} P_n^m g_m^m \leq I_m^h, 
\]

(4)

where \( I_m^h \) is the tolerable peak interference power on each subchannel. Considering the limitation of the battery capacity of D2D users, the transmission power cannot be infinite, so the transmission power satisfies the following constraints:

\[
\sum_{m=1}^{M} P_n^m \leq P_n^{\text{max}}, 
\]

(5)

where \( P_n^{\text{max}} \) is the maximum transmit power that can be provided by the \( n \)th D2D user. To maximize the energy efficiency of the D2D network and meet the communication quality of each cellular user, considering the above analysis results, the resource allocation problem based on the most energy-efficient is the following formula:

\[
\begin{align*}
\max_{a} & \quad \sum_{n=1}^{N} \sum_{m=1}^{M} \log_2 (1 + \gamma_n^m) \quad \text{s.t.} C_1: \\
\sum_{n=1}^{N} \sum_{m=1}^{M} P_n^m g_m^m & \leq I_m^h C_2: \quad \sum_{m=1}^{M} P_n^m \leq P_n^{\text{max}}. 
\end{align*}
\]

(6)

The above problem does not consider the estimation error of the channel gain; that is, it is assumed that the channel gain \( \gamma_n^m \) is accurately known. However, in actual cognitive D2D networks, with the presence of spectrum estimation errors and dynamic perception uncertainty, it is difficult to accurately obtain channel gain information. The optimal resource allocation algorithm based on traditional feedback channel information can no longer meet the needs of the actual system design. Therefore, it is necessary to take the channel estimation error into account in the algorithm design in advance, and it is particularly important to propose a robust resource allocation algorithm that can resist parameter perturbation.

3.2. Robust Resource Allocation Algorithm. Considering the influence of channel estimation error, the actual channel gain can be described by the following additive uncertainty model:

\[
\gamma_n^m = \bar{\gamma}_n^m + \Delta \gamma_n^m. 
\]

(7)

However, \( \Delta \gamma_n^m \) is a random quantity, which is the channel estimation error. Obviously, the direct assumption of \( \Delta \gamma_n^m = 0 \) is an ideal situation. However, it is not satisfactory in the actual situation. Due to the influence of the estimation error, the C1 constraint condition of the optimization problem (6) will be interrupted. Therefore, the energy efficiency optimization problem based on the interference power interruption constraint can be described as follows:

\[
\begin{align*}
\max_{a} & \quad \sum_{n=1}^{N} \sum_{m=1}^{M} \log_2 (1 + \gamma_n^m) \quad \text{s.t.} C_1: \\
\sum_{n=1}^{N} \sum_{m=1}^{M} P_n^m g_m^m & \leq I_m^h C_2: \quad \sum_{m=1}^{M} P_n^m \leq P_n^{\text{max}}, 
\end{align*}
\]

(8)

where \( \zeta_m \) is the outage probability threshold of cellular user \( m \). This problem is complex, and it is difficult to directly obtain an analysis of the resource allocation problem.

For outage probability constraints, there have been many commonly used methods to deal with, such as the relaxation probability integration method. However, in the actual cognitive D2D network, since there is no cooperation between users, it is difficult to obtain the statistical distribution information. In addition, due to the randomness of the wireless channel, the assumption of a certain probability distribution model in advance is invalid. Therefore, a new mechanism needs to be introduced to solve this problem. The minimum-maximum probability can solve the above problems well. Based on the minimum-maximum probability machine method, any interruption constraint can be described as the following form:

\[
\inf_{x \sim (\mathcal{X}, \mathcal{E})} \Pr[a^T X \leq b] \geq 1 - a, 
\]

(9)

where \( x \) is the parameter vector with uncertainty; \( a \) is the parameter vector; and \( a \) is the outage probability threshold. Based on the principle of the minimum-maximum probability machine, formula (9) can be equivalent to

\[
\sup_{x \sim (\mathcal{X}, \mathcal{E})} \Pr[a^T X \geq b] = \frac{1}{1 + d^2}. 
\]

(10)

Among them,

\[
d^2 = \inf_{a^T X \leq b} (x - \mathcal{X})^T e^{-1} (x - \mathcal{X}) 
\]

(11)

\[=
\max_{a^T X \geq b} \left( b - a^T x \right)^2 \]

\[= \frac{a^T e a}{a^T e a^T} \]

Since formula (9) can be equal to \( \sup_{x \sim (\mathcal{X}, \mathcal{E})} \Pr[a^T X \geq b] \leq a \), formula (10) can be added to it to obtain the following:

\[
a \geq \frac{1}{1 + d^2}. 
\]

(12)
Combined with formula (11), formula (12) can be obtained:

$$\max \left\{ \frac{(b - \alpha^T x)}{a^T e a}, 0 \right\} \geq f(a).$$

In the formula $f(a) = \sqrt{(1 - a)/a}$, after finishing formula (13), we can get

$$a^T x + f(a)\sqrt{a^T e a} \leq b.$$  \hspace{1cm} (14)

Equation (14) is the equivalent closed form of constraint (9), which defines the mean and variance of channel gain $g_n^m$ as $\bar{g}_n^m$ and $\zeta_n^m$, respectively. Based on the form of (14) and combined with the minimum and maximum probability machine method, the outage probability constraint $c_1$ can be converted as follows:

$$\sum_{n=1}^{N} p_n^m \bar{g}_n^m + f(\zeta_n) \sum_{n=1}^{N} (\bar{g}_n^m)^2 \zeta_n^m \leq \Gamma_n^{th}.$$  \hspace{1cm} (15)

In the formula $f(\zeta_n) = \sqrt{\zeta_n^m/(1 - \zeta_n^m)}$, therefore, the interruption interference interruption probability is converted into a closed form as shown in (15). However, due to the horizontal direction, the problem still cannot be solved. Therefore, based on Cauchy’s inequality, we can convert (15) into the following form:

$$\sum_{n=1}^{N} p_n^m \bar{g}_n^m \leq \Gamma_n^{th},$$  \hspace{1cm} (16)

where $\bar{g}_n^m = \bar{g}_n^m + f(\zeta_n)\sqrt{\sum_{n=1}^{N} \zeta_n^m}$ is a convex constraint.

The objective function is in fractional form. The problem is a nonconvex optimization problem under convex constraints. The objective function can be equivalent to

$$F(p_n^m) = \sum_{n=1}^{N} \sum_{m=1}^{M} \log_2 (1 + \gamma_n^m) - \eta \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m + Np_c \right),$$  \hspace{1cm} (17)

where $\eta$ is the total energy efficiency of D2D users and $\eta \geq 0$. Due to the coupling relationship of the transmit power in the rate function, based on the continuous convex approximation method, the transmission rate can be approximated to the following equivalent convex form:

$$\log_2 (1 + \gamma_n^m) \geq a_n^m \log_2 (\gamma_n^m) + b_n^m.$$  \hspace{1cm} (18)

In the formula, $a_n^m = \eta$ and $b_n^m = \log_2 (1 + \gamma_n^m) - a_n^m \log_2 (\gamma_n^m)$ are auxiliary variables, the initial value can be set to $a_n^m = 1$ and $b_n^m = 0$, $\gamma_n^m$ represents the last iteration value of $\gamma_n^m$.

Therefore, the objective function (17) can be equivalent to

$$F(p_n^m) = \sum_{n=1}^{N} \sum_{m=1}^{M} a_n^m \log_2 (1 + \gamma_n^m) - \eta \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m + Np_c \right).$$  \hspace{1cm} (19)

Therefore, combining formulas (16), (19), and (8), we can get the following optimization problem:

$$\max_{p_n^m, \lambda_m, \beta_n} \sum_{n=1}^{N} \sum_{m=1}^{M} a_n^m \log_2 (\gamma_n^m) + \sum_{n=1}^{N} \sum_{m=1}^{M} b_n^m$$

$$- \eta \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m + Np_c \right) \text{s.t.} C_1;$$  \hspace{1cm} (20)

$$\sum_{n=1}^{N} p_n^m \leq \Gamma_n^{th}.$$  \hspace{1cm} (21)

Equation (20) is an optimization problem, and the Lagrange function can be used to obtain an analytical solution for resource allocation.

The Lagrange principle can be used to solve problem (20), and the Lagrange function to construct the optimization problem (20) is as follows:

$$L(p_n^m, \lambda_m, \beta_n) = \sum_{n=1}^{N} \sum_{m=1}^{M} a_n^m \log_2 (\gamma_n^m) - \eta \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m + Np_c \right)$$

$$+ \sum_{n=1}^{N} \sum_{m=1}^{M} b_n^m + \sum_{m=1}^{M} \lambda_m \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m \right) - \sum_{n=1}^{N} \beta_n p_n^{max}.$$  \hspace{1cm} (22)

In the formula, $\lambda_m \geq 0$ and $\beta_n \geq 0$ are Lagrangian dual variables. Equation (21) can be equivalently described as follows:

$$L(p_n^m, \lambda_m, \beta_n) = \sum_{n=1}^{N} \sum_{m=1}^{M} L_{n,m}(p_n^m, \lambda_m, \beta_n) - \eta Np_c$$

$$+ \sum_{n=1}^{N} \sum_{m=1}^{M} b_n^m + \sum_{m=1}^{M} \lambda_m \left( \sum_{n=1}^{N} \sum_{m=1}^{M} p_n^m \right) - \sum_{n=1}^{N} \beta_n p_n^{max}.$$  \hspace{1cm} (23)

Therefore, for every D2D user,

$$L_{n,m}(p_n^m, \lambda_m, \beta_n) = a_n^m \log_2 (\gamma_n^m) - \eta p_n^m - \lambda_m p_n^m \bar{g}_n^m - \beta_n p_n^m.$$  \hspace{1cm} (24)

According to the Lagrangian duality principle and formula (21), the dual problem is as follows:

$$\min_{\lambda_m, \beta_n} D(\lambda_m, \beta_n) \text{s.t.} \lambda_m \geq 0, \beta_n \geq 0.$$  \hspace{1cm} (25)

The expression of the dual function is as follows:

$$D(\lambda_m, \beta_n) = \max_{p_n^m} L(p_n^m, \lambda_m, \beta_n).$$  \hspace{1cm} (26)

According to the KKT condition and the subgradient update method, the analytical solution of the resource allocation algorithm can be obtained as follows:
\[ \hat{P}^{m,n} = \ln(\eta + \delta_m g_n^{m,n} + \beta_n) \]

\[ \lambda_m(t + 1) = \left[ \lambda_m(t) - s_1 \times \left( I_m^{th} - \sum_{n=1}^{N} P^{m,n}_n \right) \right]^{+}, \]

\[ \beta_n(t + 1) = \left[ \beta_n - s_2 \times \left( \sum_{m=1}^{M} p_n^{max} - \sum_{m=1}^{M} p_n^m \right) \right]^{+}, \]

\[ \eta = \sum_{n=1}^{N} \sum_{m=1}^{M} \log(1 + \gamma_n^m(p_n^m)) \]

The formula, \( s_1 \) and \( s_2 \) are the iteration steps and \( [x]^+ \) is the number of iterations. When an appropriate step factor is set, the algorithm can converge quickly.

3.3. Analysis of Simulation Results. The path loss index is 4, the shadow fading coefficient is 8 dB, the maximum transmit power threshold for D2D users is \( p_n^{max} = 23 \) dBm, the circuit power consumption is \( p_c = 12 \) dBm, the noise power is \( N_0 = -114 \) dBm, the number of D2D users and cellular users is \([2, 50]\), and the interference power threshold value is \( I_m^{th} = -30 \) dBm, respectively. Without loss of generality, each of the subchannel is considered as a unit bandwidth in the simulation.

Figure 2 shows the relationship between the energy efficiency of cognitive D2D network users under different numbers of users. It can be seen from the figure that the total energy efficiency of the system increases as the number of D2D users increases. However, when D2D users increase exponentially, the energy efficiency of the system does not increase exponentially. The reason is that the cochannel interference between multiple D2D users will increase the interference of the currently active users, thereby reducing the signal-to-interference and noise ratio of the users in the existing network. In addition, the robust algorithm in this paper is more energy-efficient than the traditional nonrobust algorithm. As the outage probability threshold increases, the energy efficiency of the algorithm in this paper gradually increases. A large interruption probability threshold means that the effective transmission power in the interference power constraint is reduced, thereby providing better protection performance for cellular users.

Figure 3 shows the relationship between the total energy efficiency of D2D users and the outage probability threshold. It can be seen from the figure that as the variance of the channel gain error increases, the total energy efficiency of D2D users increases, because it can be seen from the interference power constraint that as the channel gain estimate increases, \( C_n^m \) increases, and the effective transmission power decreases to avoid harmful interference to cellular users. Therefore, power consumption is reduced and system energy efficiency is increased. In addition, the energy efficiency of the traditional nonrobust algorithm remains constant, because the outage probability of zero will make the second term of the robust interference constraint independent of the variance of the channel gain estimation error, so it remains constant. From the figure, it can be found that as the interruption probability threshold allowed by cellular users increases, the total energy efficiency of D2D users also increases. As the probability of interruption is increased, the value of the second term is increased, thereby reducing the effective transmission power and reducing the total energy consumption.

Figure 4 shows the energy efficiency performance comparison of different algorithms under different transmit powers, where the number of D2D user pairs is 2. It can be seen from the figure that as the maximum transmit power
threshold of D2D users increases, the total energy efficiency of D2D users gradually increases, because increasing the user threshold can allocate more power to each subchannel to improve user rate and energy efficiency. In addition, the energy efficiency of the robust algorithm in this paper is higher than that of the traditional nonrobust algorithm. Therefore, to improve the robustness of the system and the transmission of delay-tolerant services, the algorithm in this paper allows users to have a certain tolerance to the probability of interruption, and its maximum transmission power is greater than that of traditional nonrobust algorithms. From the perspective of different outage probability thresholds $\xi_m$ and estimated error variance, as the outage threshold increases, its energy efficiency gradually increases; as the estimated error variance increases, the total energy efficiency of D2D users increases. As the estimation error increases, the estimated channel gain value will deviate from its true value more and more, so it is necessary to increase the transmission power to overcome the influence of this part of the channel uncertainty on cellular users, thereby increasing the energy efficiency.

Figure 5 shows the total energy efficiency of D2D users under the maximum interference power of different algorithms. The outage probability and the estimated error variance are set to 0.05 and 0.01. It can be seen from the figure that the algorithm in this paper has a higher energy efficiency performance than the traditional nonrobust algorithm. As the maximum interference power allowed by cellular users in each subcarrier increases, the total energy efficiency of D2D users decreases. As the increased interference power can allow D2D users to transmit more power on the shared subchannels, thereby increasing power consumption and reducing overall energy efficiency, it is necessary to balance the relationship between transmission rate and energy consumption. To more intuitively reflect the advantages of the algorithm in this paper, the following analysis is shown in Table 1. It can be seen from the table that the robust algorithm in this paper has a performance improvement of close to 2% to 3% in energy efficiency performance, indicating that the algorithm in this paper has better energy efficiency performance, and as the feasible range of the transmittable rate increases, that is, the maximum transmits it power threshold of D2D users, the magnitude of this energy-efficiency performance improvement will further increase.


4.1. Research Object Selection. The distribution and collection of the questionnaire were completed in November 2019. A total number of 220 questionnaires were distributed in this survey, and a total number of 215 questionnaires were returned, including 200 valid questionnaires. Based on the data obtained from the survey, the relationship between hotel employees’ emotional labor, job burnout, and job satisfaction is studied. The effective response rate was 93. The following is a descriptive analysis of the sample (see Table 2).

Judging from the available data, women accounted for the majority of the respondents, 108, accounting for 58.4% of the total; in terms of age, the population aged 21–30 years old was the largest, 138, accounting for 49.7%. In terms of marital status, the majority of unmarried people are 135, accounting for 73%. In terms of academic qualifications, the subjects with a high school and college degree or above are the most, and the samples are unevenly distributed among...
Among them, the catering department has the most subjects, with 132 people, accounting for 71.4%.

4.2. Descriptive Statistical Analysis. To grasp the overall distribution of the sample, this study conducted a descriptive statistical analysis of the emotional labor, job burnout, and job satisfaction of the sample. The results are shown in Table 3.

4.3. Correlation Analysis of Emotional Labor, Job Burnout, and Job Satisfaction. The frontline employees of the hotel will adjust their inner emotions to meet the requirements of the workplace as much as possible. The results show that the standard deviation is small, indicating that the difference between the variables is not large. In this article, we analyzed the relationship between emotional work, job burnout syndrome, and job satisfaction.

This section explains whether there is a clear relationship between emotional labor, superficial behavior, deep behavior, and job satisfaction. The results are shown in Table 4.

Table 4 shows that emotional job depth behavior is significantly positively correlated with job satisfaction, while the correlation coefficient is significantly negatively correlated with surface behavior and job satisfaction. Therefore, there is no clear correlation.

In this part, we will analyze two aspects of emotional labor as follows: superficial behavior and deep behavior, and job burnout in three aspects as follows: emotional fatigue, depersonalization, and sense of accomplishment to test the correlation. The results are shown in Table 5.
This part will be discussed from five aspects: job burnout, emotional exhaustion, depersonalization, low sense of achievement, and job satisfaction.

Correlation analysis was performed to test whether there is a significant correlation, and the results are shown in Table 6.

4.4. Measures to Improve the Effect of Emotional Management in the Hotel Industry. Regression analysis shows that the superficial behavior of hotel employees has a positive effect on emotional exhaustion and depersonalization but has no obvious effect on job satisfaction. Low job burnout will hurt job satisfaction, while emotional fatigue and depersonalization will not directly affect job satisfaction. Hotel managers cannot ignore this, seeing that it makes employees’ emotional labor behavior smooth and tends to deepen performance strategies to prevent job burnout and improve job satisfaction. Combining the above research conclusions, we propose the following countermeasures: as an employer of hotel employees, hotel managers should pay attention for raising awareness of emotional management. Managers should pay close attention to the emotional labor of employees and combine the improvement of service quality with the mental health and emotional state of hotel employees. Timely communication and encouragement between hotel managers and service staff, especially during busy customer service hours, play an important role in encouraging the emotional initiative of the hotel staff. For hotel employees, especially for positions with high emotional labor, hotels facing daily emotional labor problems should use the emotional awareness and control ability of employees as an important selection indicator when hiring employees. Clarify emotional labor content in job responsibilities.

The job responsibilities list all the work tasks to be completed in a certain position, the equipment and materials

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<th>Table 4: The correlation between emotional labor and job satisfaction.</th>
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<td><strong>Pearson correlation</strong></td>
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<td><strong>Significance (bilateral)</strong></td>
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<td><strong>Surface behavior</strong></td>
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<th>Table 5: Correlation matrix between emotional labor and job burnout.</th>
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<td><strong>Low sense of accomplishment</strong></td>
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needed for the working environment, and important information related to the job. Traditional job responsibilities focus more on formal standardization and detailed job descriptions while ignoring the needs of employee development. To reflect the personal values of employees, it is necessary to appropriately adopt a “role-based” game method to reflect employees’ emotional issues in the work, enrich the work content, and change the strict work standards. Hotel performance evaluation should not only focus on the daily workload of employees but also consider the emotional contribution of service personnel in the service process. Based on the traditional wage system, hotels can establish an emotional labor standard system that conforms to the characteristics of the hotel industry and quantify various indicators.

5. Conclusion

This research divides emotional work into emotional labor strategies and emotional labor needs. From the perspectives of labeling rules and interactive expectations, the related content of emotional labor needs is integrated. The maturity scale is established from two perspectives. This division method separates the system rules of emotional work from the actual needs that employees must meet in the process of emotional work. This is the basis for dividing emotional labor demand in this research. It analyzes the role of identity theory on individuals, connects emotional labor requirements with emotional labor strategies, and proposes that identity can be used as an intermediary mechanism for the relationship between parameters. Studies have shown that emotional labor demand has a positive effect on job burnout syndrome. Deep and superficial behavior is a complete mediator of emotional labor demand and job burnout syndrome. Natural adaptability cannot be mediated, but this is the end of the mediation path, and it has an inhibitory effect. The direct impact of emotional labor requirements on job burnout syndrome is meaningful only in natural coordination. Actively regulate the relationship between employees’ emotional work needs and employees’ superficial and deep roles, which can better regulate interpersonal relationships.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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