Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

A DCGNET based Novel Approach for Employee Engagement Mediated Progressive Work Practices on Logistics Organization

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Abstract. The purpose of the research was to ascertain what aspects of a dynamic workplace were most influential in shaping levels of participation, commitment, and inspiration among workers. This study focuses on IT firms in Chennai, India, and uses a qualitative and descriptive approach. Academic studies on subjects including higher productivity, enhanced communication, a more collaborative work culture, and the eradication of human error and bias were reviewed to determine the impact of a progressive work environment on employee engagement. The suggested strategy makes use of preprocessing, feature extraction, and model training. The raw data requires a preprocessing procedure to organize it. We use word embeddings and term frequencies for feature extraction. The models are trained using DCGNet once the features have been retrieved. CNN and GRU, two of the most popular alternatives, are beaten by the proposed strategy.

Keywords: *Employee Engagement (EE)·High Performance Work Systems (HPWS)·Gated Recurrent Unit (GRU).*

1 Introduction

In today's competitive corporate environment, success often hinges on intangible qualities like creativity and invention. The seeds of new services, goods, solutions, and processes are planted when an organization cultivates an atmosphere that stimulates and rewards creative thought. The concept that innovative activities stem from both natural characteristics and an individual's attitude towards their professions has led to increased scholarly focus on the attitudinal factors that help induce inventive activity. One of these components is "engagement," which is defined as "the intensity and direction of cognitive, emotional, and behavioral energy." For the simple reason that the inventive process is three times as taxing on the human body. Further, academics agree that the various individual and organizational factors that motivate innovative activity in the workplace have been understudied. While it's true that however, these results can only paint a partial picture because they are still bound to the contexts in which they were initially gathered lacking cohesion all around. Variables, their connections, and the ideas they represent stand on their own as illuminating. However, by seeing them as a whole, one might gain a more complete understanding. In order to develop a whole method for, we perform a comprehensive literature review. Human resource managers are always thinking of new ways to motivate and inspire their teams to work harder and more efficiently in the face of adversity. When workers are fully engaged in the company's mission and values, they are more likely to go above and above on a regular basis. When workers are happy with their work environment, they are more willing to go above and beyond for the organization. This has a multiplier effect on the business in the form of satisfied customers, a larger market share, and higher revenue. The greatest challenge in discussing the term "engagement" in theoretical literature is the lack of a universal definition of employee involvement. Based on studies conducted, "involvement" means being "present" when on the clock at work. Employees are more invested in their jobs when they have work that has meaning to them, when they feel safe at work, and when they have opportunity to make a difference. Participation, as further investigated, demonstrates that actors employ and express their full selves (emotions, thoughts, and bodies) in their performances. The cognitive dimension includes the perspectives of staff, management, and the organization as a whole. When we discuss the sentiments of the workforce, we are referring to their views on the company and its management. Both academics and industry professionals agree that employee engagement is a crucial issue in modern management. It stands to reason that companies who invest in their employees will reap the benefits in areas such as profitability and customer satisfaction; and that engaged workers will be more productive and happier at work. Another definition of "unique, value-creating organizational capability" is "collective organizational engagement," or the "shared perceptions of organizational members that members of the organization are, as a whole, physically, cognitively, and emotionally invested in their work." It has now been widely acknowledged that a highly motivated staff is a key competitive advantage. The term "employee engagement" refers to "the state of having all of one's mental, emotional, and physical resources directed towards doing one's job". By exploring the dynamic between employee engagements, employer branding (as measured by perceived employer attractiveness), perceived organizational support, and satisfaction with internal communication, this study aims to advance theoretical understanding of these and other concepts in internal communication. Putting all of these things under the purview of internal communication may make administration of them easier. Engagement has emerged as the paradigm through which organizations integrate, connect, and work with numerous stakeholders as a result of the evolution of relationship management in public relations. The competitive advantage and market differentiation of modern organizations rely heavily on their employees' level of enthusiasm and commitment to their work. Modern businesses have a double-edged sword: they have a responsibility to their shareholders to maximize profits, but they also have a social obligation to contribute to the communities in which they operate. Businesses can't stay in business if they don't fulfil their social contract obligations by benefiting society as a whole. In an attempt to align corporate goals with society values and aspirations, many new academic fields have evolved in the last few decades. Standards in ESG (environmental, social, and governance), sustainability, corporate purpose, and corporate social responsibility (CSR) are all part of this. Data analysis on employee attitudes, performance, and behavior can provide organizations with useful insights about employee engagement and ways to improve it. When it comes to determining a company's success, employee engagement ranks first. Studies have shown that companies with enthusiastic personnel produce 45 percent higher output. Using state-of-the-art algorithms and machine learning, companies can gain a better understanding of their employees' satisfaction levels and what drives them. With this information in hand, targeted programs to increase engagement and retention can be created. Machine learning increases the likelihood of exceptional corporate performance by a factor of three and increases the likelihood of improved employee engagement by a factor of two, according to Deloitte's analysis of employee data. Machine learning is thus rapidly becoming into a powerful tool for business development, with huge benefits for employers and employees alike. An excellent chance to tap into employee engagement is presented by HR analytics. Managers may now more easily monitor their employees' mental health and see how it impacts the bottom line thanks to artificial intelligence. Artificial intelligence (AI)-powered systems can detect trends in workers' actions in hybrid work modes, enabling the collection of useful information. It shows how engaged employees are right now and points them in the right way for future engagement improvements based on data-driven insights and sentiment analysis. Government programmes sought at "bringing the public interest back into the private domain" are being complemented by business self-regulatory initiatives, such as the United Nations' Global Compact and the Sustainable Development Goals. Even though the public and private sectors are collaborating to solve society's most pressing issues and promote the common good, some still question if we're truly achieving progress. And found that 8% of Germans and 7% of Swiss believe that the common good is not being given enough consideration.

2. Literature Survey

China's economic growth, urbanization, and modernization over the past three decades have been nothing short of astounding. [1]China's economy has benefited from the rapid growth of its small and medium-sized enterprises (SMEs).

Eighty percent of working Chinese citizens are currently engaged by micro, small, and medium-sized enterprises. [2]The fact that SMEs are governed by fewer regulations than large enterprises is a major factor in their success. Poor pay and a hostile work environment marked by harassment, bullying, and social marginalization are commonplace in small and medium-sized firms (SMEs).However, everyone may agree that those who have witnessed or suffered violence have no right to joy. What does "employee well-being" entail? To the good feelings people get when their wants and needs are both satisfied [3].However, a climate factor that damages a person's sense of security is a toxic workplace atmosphere, which is associated with higher absenteeism and reduced productivity to be harmful to one's physical or emotional well-being. Organizational support is also essential contributor to the morale of the workforce. Despite the fact that a great deal of study has been done on the Despite a growing corpus of literature on the mental processes that increase worker engagement [4], no institution-centric description of factors that encourage learning inspire taking chances and developing as individuals. This word describes the atmosphere created by the interactions of employees in an unhealthy workplace as well as in the professional realm [5]. In the past, there were two primary varieties of workplaces: both effective teamwork and counterproductive office politics were discovered to occur.The current pandemic crisis has made it challenging for firms to manage their human resources. According to [6], the prevalence of remote work is growing, and new policies and practices are being implemented to limit employee contact. Last but not least, layoffs, wage cuts, and furloughs have exacerbated employment instability and economic loss. The anxiety levels of workers are on the rise. Workers are in grave danger from the accumulative effects of persistent stress on the job [7]. Here, businesses are faced with the challenge of adapting to new health rules and practices protect your physical and mental health [8]. Consequently, it's reasonable to assume that personnel administration is an issues are more challenging than they were before the pandemic. These measures are designed to boost joy and speed up the healing process as well as increasing efficiency inside the business. In [9], researchers confirmed the positive correlation between an engaged workforce and lower rates of absenteeism. As was illustrated above, this is related to worker happiness and morale affect productivity, efficiency, and effectiveness in a positive way [10].However, in order to get there, we must first solve the organizational a corporation needs to be quick on its feet and resilient in order to make it through a pandemic workforce that is both capable and resilient, with active engagement being essential [11].Despite the fact that an organization's crisis response to an external event, such as a war or a pandemic in the country where it is headquartered, can have a positive effect on employees' affective commitment to the organization, research shows that "an employee's perception that the organization values his or her work contributions and cares about the employee's well-being" [12] is a key factor in employee engagement. Several studies have focused on the following three factors related to employee loyalty: commitment to one's principles, one's beliefs, and one's emotions [13]. To be "affectively committed" to an organization means to feel an emotional investment in its success, as defined by [14] that arises from belonging to and actively participating in a community organization. There are two main ways in which affective commitment is distinct from normative and continuing commitment. Happiness at work, dedication to one's organization, and other advantages result taking part [15].Suppose mental a corporation that invests in its employees will foster an environment where employees are resilient and enthusiastic about their work as vigor or force. On the other hand, dedication takes into account factors like drive, challenge, and reward work that gives one purpose, engagement, and enthusiasm. Finally, absorption occurs when employees are fully committed to the activity at hand, keeping their concentration intact as the clock winds down rapid evolution makes it hard to tear themselves away from their jobs [16]. Conditional variables some of the factors that have previously influenced employees' involvement in surveys are mentioned. Human resource management (HRM) in the clear, diversity management, and organizational integrity, leadership, and organizational zeal mediation and arbitration assistance they receive on a personal level from the company. Research conducted in the banking sector in Bangladesh [17] provides further evidence for the importance of transformative leadership in increasing productivity and fostering employee engagement. This indicates the efficacy of transformative leadership in enhancing employee motivation and output. Strong correlations have been shown between transformational leadership and enthusiastic participation in the workplace [18]. Employees are more prone to participate in extra-role conduct if they do not feel like they belong to the business and if their managers and supervisors do not use supportive and effective leadership styles. One of the roles of a transformational leader is to inspire team members to develop their own methods for boosting efficiency on the job. [19] Thus, COR theory is employed to provide light on the connection between transformative leadership and employee engagement. The outcome is a decrease in their feeling of group identity and respect for the group's leaders leading to a dispassionate workforce. Despotic leadership distracts from work, which is stressful and is often viewed as risky employment as a matter of survival [20], hence decreasing worker engagement. The results of recent studies Statistics from the service sector reveal that abused women are disproportionately represented in the likelihood of being unhappy in one's job rises. Those who are targeted by aggressive when they are mistreated by their superiors, they can become severely depressed and physically weak solidarity amongst one's coworkers. [21] Those that suffer abuse Tyrannical leaders operate in this way because they are obsessed with protecting the country's most prized possessions task using a number of strategies (including silence). Later social exchange theory built on a foundation of synthesized sociological and social psychology theories. The primary emphasis of is on the methods of behavioral psychology. [22]The groundwork for what would become known as "The Social Psychology of Groups" hypothesis. This theory extensively examines concepts from the domain of psychology. Aims to look at economic and technological elements, unlike the other writers mentioned. Despite being distinct areas of study, all three agree that social exchange is fundamental. [23]To rephrase, this theory is based on two processes: contingent and rewarding, which need "transactions" or "exchange" as its building blocks. Human resource social behavior, can be studied via the prism of behavioral psychology. Theory of person-organization fit delves into the motivations and outcomes of interactions between companies and their staff. A high level of -P-O fit is demonstrated when the organization maintains its adaptability and dedication in the face of adversities. [24]Separating and defining supplementary fit from complimentary fit would be a fantastic piece of content. Employees are seen as having complementary qualities if they "supplements, embellishes, or possesses characteristics" that are similar to another employee's. An individual's environment is said to have "made whole" their personality when there is a complimentary fit. In a nutshell, P-O fit includes both requirements and demands. When a company provides what its customers want, it achieves the -P-O fit from a needs-supplies viewpoint. [25]Employer branding theory combines ideas from marketing management with those from human resources. When a business promotes itself as an employer by providing its employees with a variety of perks, both material and immaterial, it is engaging in employer branding. While this idea can be used to current employees as well, the ideas presented thus far are primarily focused on prospective candidates when we talk about the EA. This has resulted in an abundance of studies about EA: The most important EA values are what state that students prioritize two things: the importance of learning and progress, and the recognition of EA. To illustrate the point, provided eight criteria for evaluating IT professionals.

3. Proposed System

In this proposed approach to investigate the relationship between diversity practices and one of the most important measures of employee satisfaction loyalty to the company. It was speculated that a stronger mediation link between trust atmosphere and the association with diversity practices may be achieved through employees' feelings of belonging in the workplace.

3.1 Preprocessing

In order to reduce feature variance, the data is preprocessed after loading is complete using steps such as stemming, case folding, tokenization, and stopword elimination. As a first step in preprocessing, remove characters from letters a-z, fold letters, and convert all words to lowercase. Word by word, every sentence in the document is processed in the second stage called tokenization. Later on, we eliminate unnecessary words called "conjunctions" and "clothing" to eliminate stopwords [26]. Transforming words into their basic forms is the goal of word stemming, the last preprocessing step. Unsupervised learning methods like topic modeling rely heavily on high-quality data input. This can be achieved by the use of preprocessing to clean up the raw data. The gaps in knowledge are filled in first. Then, the steps below are taken to sort through the results:

3.1.1 Remove Anonymization

Scorius removes phrases like "company" because they no longer provide any context after being anonymized.

3.1.2 Tokenization

Words in documents are treated as if they were a "bag of words" in this paradigm. With tokenization, phrases are broken down into their individual words without regard to their original arrangement.

3.1.3 Remove punctuation, separators, numbers and symbols

These characters are removed because they offer nothing to the text's meaning and complicate analysis.

3.1.4 Lowercase

All uppercase letters are changed to lowercase ones for consistency's sake.

3.1.5 Stop words removal

Stop words are typically omitted from text analysis since they do not contribute to a fuller understanding of the text [22]. Getting rid of these words reduces the size of the vector space, which speeds up execution. Overall, it helps increase productivity.

3.1.6 To get rid of terms with less than 3 characters

Words that are merely one or two characters long are not included because of their limited semantic relevance and the noise they bring to the data.

3.2 Feature Extraction

Text feature extraction is a technique for generating characteristics from text data that can be used by a classifier. In this proposed to take a close look at how different methods of feature extraction fare under scrutiny. The preprocessing results will be weighted and recorded in vector representation before being used as input in the classifier [23]. Higher-scoring words and phrases have made more substantial contributions. Text feature extraction initially generates a vocabulary list from the input text to utilize as features in a classifier. The results of the preprocessing will be used to weight and store vector representations of the features that will be fed into the classifier. You can put a number on how much weight a certain word or phrase should have in determining the document's category.

3.2.1Term Frequency

The current document's word count is reflected using a metric known as Term Frequency (TF). Combining the keyword frequency with the Inverse Document Frequency (IDF), which is the score of terms across all texts, helps lessen the weight of overused words in the corpus. This grade might help bring out the special words that convey the necessary information in the document. The IDF for the latter is reduced since the former is less frequent. There are primarily three approaches to discuss TF: Assigning a value of 1 to each word within the document and a value of 0 to each word outside the document using binary value. The concept in question does not consider the frequency with which specific words appear. Achieving TF status through reliance on word frequency alone. Normalized fractional value is the phrase used.

3.2.2Word Embedding

Each word is given its own dimension in a sparse vector space by means of word embedding. The model discussed here is an effort to approach this problem from a fresh perspective; it may be thought of as a word embedding algorithm. Natural language processing employs word embedding to lower the dimensionality of vector representations. The term refers to the mapping from a high-dimensional space to a continuous vector space with less dimensions. Some researchers in machine learning argue that only a subset of these methods can properly be referred to as "word embeddings," despite the fact that the name "word embedding" incorporates topic models, semantic distribution models, and neural language models.

3.2.3 PCA

Principal component analysis (PCA) helps to reduce the dimensionality of the variates and filter out noise by replacing them with low-dimensional principal components. The nonlinear principal component that PCA produces is essentially the combination function of the original variables. The low-dimensional main components used as inputs to the model are not suitable for regulating the sintering process in a rotary kiln since they are not physically significant and cannot be theoretically understood [27].

To select the most appropriate input variables, one can use the component matrix that principal component analysis (PCA) produces to see how the original variables are related to each PC.

3.3 Model Training

3.3.1 DCGNet-Framework

DCGNet is fed the remaining thermal process variables between $l - \varepsilon$ and l after principal component analysis has been used to reduce the number of variables. The integration of CNNs and GRU allows us to extract multivariate coupling and nonlinear dynamic characteristics. We also look at the nonlinear dynamic aspects of the classic ST using a parallel GRU [28]. By working in tandem, they feed precise outputs from deep feature extraction into the FC layer, enabling it to foretell

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

the ST at time $l+1$. In the next three sections, we'll dive deeper into the specific network layers used by DCGNet.

3.3.2 Extraction of Features from Multivariate Coupling Module:

Two convolutional neural network (CNN) layers are used, with an emphasis on the coupling properties of the many process variables. They directly feed the selected temperature data into a 2-D convolutional layer (2-D CNN) and take advantage of the CNN's two most critical aspects, local perception and weight sharing, to extract local spatial coupling correlations among the multi variates. A $(\varepsilon+1)\times(h+1)$dimensional $Qw=\big[[Q(l),\dots,Q(l-\varepsilon)],[w(l),\dots,w(l-\varepsilon)]\big]$serves as input to the CNN layer. Optimal process variables, h, are identified through principal component analysis. Multiple filters, the total breadth of which is proportional to the number of variables, are used by the 2-dimensional convolutional neural network (CNN). The Qw input matrix is swept by the filters, and new values are generated.

$$n_{rt}^{H}=ReLU\left(y_{s\times(h+1)}^{H}*Qw+\delta^{H}\right) \tag{1}$$

where represents the convolution operation, and $y_{s\times(h+1)}^{H}$ represents the filter weight for the H th filter of dimension $s\times(h+1)$. For the convolutional layer, H represents the bias. ReLU is defined mathematically as$(q)=\max(0,q)$. The output of the 2-D CNN is of size $1\times t$when boundary filling is ignored, with $t=\frac{(\varepsilon+1)-s}{j}$where s is the step length. Multiple filters, such as a 1-D convolutional layers (1-D CNN) sweep through the vectors once yet again from top to bottom in a certain step, further refining the features while decreasing the number of model parameters and improving the operation speed; the time and space coupling features n_{rt} are compressed in the following way.

$$N^{E}=ReLU\left(\sum_{r=1}^{H}Y^{E}*n_{rt}^{E}+\delta^{E}\right) \tag{2}$$

The number of filters, E, that will be used. Two cycles of convolution computations refine the spatial-temporal coupling features of specific process variabilities. The GRU gets around the RNN's problems with capturing long-term dependencies by using perceptron memory units and gate functions to recover the prior data. After extracting features using two convolutional layers, a GRU layer is used to recall the evolution of a number of independent variables. In order to calculate a GRU cell's final secret state at time l, we use the formula

$$i_{l}=\omega\left(y_{i}n_{l-1}^{Qw}+u_{r}N_{l}+\gamma_{i}\right) \tag{3}$$

$$p_{l}=\omega\left(y_{p}n_{l-1}^{Qw}+u_{r}N_{l}+\gamma_{p}\right) \tag{4}$$

$$\tilde{n}_{l}=\tan n\left(y_{n}\left(y_{n}\odot n_{l-1}^{Qw}\right)+u_{n}N_{l}+\gamma_{n}\right) \tag{5}$$

$$n_{l}^{Qw}=\left((1-p_{l})\odot n_{l-1}^{Qw}+p_{l}\odot\tilde{n}_{l}\right) \tag{6}$$

where y, u, γ bias, $\tan n$, $\odot$elementwise multiplication, and ω sigmoid are weight matrices, and where tan(n) is the hyperbolic tangent function.

The functioning of the i_{l} reset gate and the p_{l} update gate are represented by Equations (3) and (4). One can calculate the likelihood of an update or reset by feeding the current result N_l and the state that is hidden n_{l-1}^{Qw} from the previous time step into a function called sigmoid. The new memory content $\tilde{n}_l$ is the result of nonlinear interactions between the present data at time step N_l and the portion of the previous hidden state chosen by the reset gate i_l. The current dynamic coupling information n_l^{Qw} is computed by (6) using the newly recorded data $\tilde{n}_l$ and the state that was hidden from the previous time step n_{l-1}^{Qw}. Taking use of the nonlinear representation of the spatiotemporal coupling characteristics, the FC-layer-1 that comes after the GRU layer is able to unearth more precise deep feature information. The formula for the N^{Qw} output of a series of GRU layers is

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$$B^{Qw} = g\left(y_{Qw}N^{Qw} + \gamma Qw\right) \tag{7}$$

where y_{Qw} is the weight matrix and Qw is the bias vector of FC-layer-1. Multivariate variables exhibit a nonlinear space-time coupling in the form of B^{Qw}.

3.3.3 EE Extraction Module Dynamic Characteristics:

To accurately record the EE time series' nonlinear dynamic features, a parallel GRU layer is employed. This layer performs the same job as a serial GRU layer but receives distinct inputs. The GRU layer takes as inputs the EE data collected over time $\{w(l), \ldots, w(l-\varepsilon)\}$. The GRU then makes use of the feedback structure to log the timestamps of the earliest occurrences of unusual changes in the cellular EE sequential data [24]. The nonlinear dynamic characteristics N^w of the EE can be acquired with each step update thanks to the parallel GRU layer's activity.

3.3.4 EE Extraction Module Dynamic Characteristics:

Line nonlinear regression is used to create DCGNet's final outputs following FC-layer-2 feature extraction for weighted fusion of the two modules' outputs.

$$\tilde{w} = g(y_B)B^{Qw} + y_w N^w + \gamma_{Ga} \tag{8}$$

where $\tilde{w}$ is the predicted output of the model, y_B and y_w are the weight matrices, y_w is the bias value, and g is a nonlinear activation function.

4. Result and Discussion

Managers in the field of human resources now place a premium on the enthusiasm and dedication of their staff. This study adds to the current literature by exploring the impact of HPWS on employee attitudes and, secondarily, employee engagement in China, in light of recent research demonstrating HPWS have broad applicability in today's globally interconnected business world. The connection between HPWS and staff commitment is moderated by employees' positive emotions and their level of job satisfaction.

TABLE I. PERFORMANCE METRICS.

METRICS	PRECISION	RECALL	F1-SCORE	ACC
GRU	90.77	89.24	91.24	91.69
CNN	92.65	91.03	93.89	94.34
DCGNet	96.38	95.41	98.04	98.51

According to the data in Table I, the DCGNet model is superior for determining whether or not an employee will be promoted, and the DCGNet imbalanced technique achieves the best classification performance (an accuracy of 98.51%) when used for this purpose.

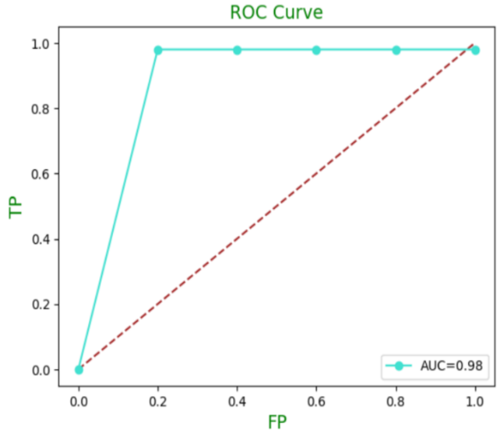

Fig. 1. ROC Curve of the Model

Figure 1 displays the model's ROC Curve. Rates of false positives were plotted on the x-axis, while those of real positives were plotted on the y-axis. The Area Under the Curve (AUC) is 0.98.

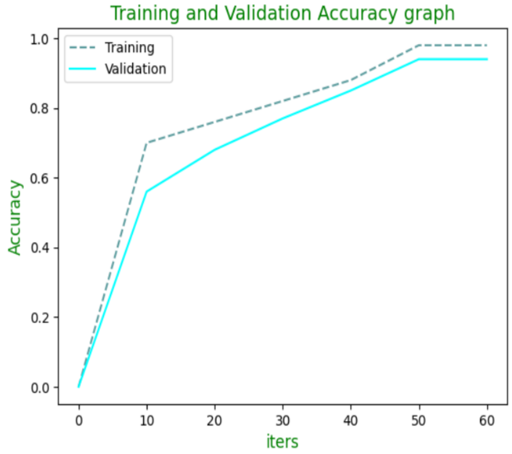

Fig. 2. Training and Validation accuracy of the Model

Figure 2 displays the accuracy curves for each iteration of the model. The y-axis shows the percentage of correct answers, while the x-axis shows the total number of iterations. After 50 iterations, training is as accurate as it can get. Accuracy throughout training and validation is 0.98 and 0.94, respectively.

Fig. 3. Training and Validation Loss of the Model

Figure 3 shows that the optimal classification effect is reached after five rounds of training (60 iterations). Loss throughout training and validation is 0.8 and 1.0.

5. Conclusion

Finding the negative consequences of a TWE on productivity and morale in the workplace was the primary goal of this research. This research paradigm was developed with concepts from the literature on resource conservation and organizational sustainability in mind. According to the study's theoretical framework, a toxic work environment has a detrimental effect on employee engagement in both direct and indirect ways (through organizational support and employee well-being). In order to make sense of the raw data, some sort of preprocessing step is required. In order to extract features, we make use of word embeddings and phrase frequencies. DCGNet is used to train the model based on the recovered features at the end. The suggested strategy outperforms both the CNN and GRU models in terms of accuracy, with an average of about 98.51 percent.

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