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ORIGINAL RESEARCH

Adversarial training with GatedTabTransformer and the GAN to predict re-employment factors of Korean male workers after an industrial accident

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Abstract

Background: The re-employment of male workers after an industrial accident is a critical problem with substantial socioeconomic implications. This study proposes an advanced predictive model integrating the GatedTabTransformer with the generative adversarial network using adversarial training to improve the accuracy and robustness of re-employment predictions. **Methods**: We compared the performance of the proposed model against traditional machine learning techniques, including logistic regression, *k*-nearest neighbors, support vector machine, linear discriminant analysis, random forest, bagging, adaptive boosting and extreme gradient boosting on a dataset of 1383 male workers after an industrial accident. **Results**: The proposed model outperforms these traditional methods across the performance metrics, achieving an accuracy of 89.2% and an area under the receiver operating characteristic curve of 0.924. Furthermore, the analysis identified previous employment duration, age, injury severity, education level, and industry type as the most significant factors influencing re-employment. **Conclusions**: These findings underscore the potential of advanced machine learning techniques in addressing complex real-world problems and provide actionable insight for policymakers and practitioners focused on improving re-employment outcomes for male workers after an industrial accident.

Keywords

Adversarial training; GatedTabTransformer; Generative adversarial network (GAN); Re-employment prediction; Korean worker; Industrial accident

1. Introduction

Industrial accidents are a serious social problem that significantly impairs the financial and mental well-being of affected employees and their families [1]. Re-entering the workforce presents significant challenges for those who have suffered from such accidents and face a temporary or permanent loss of work capabilities [2]. Past studies on this subject have primarily employed statistical analysis methods to pinpoint the variables affecting male employees' ability to find new jobs after suffering an injury. However, these conventional approaches have several critical drawbacks [3]. First, considerable research has predominantly depended on elementary statistical methods, such as logistic and linear regression [4]. These techniques do not provide ideal predictive performance because they cannot fully capture the complex nonlinear relationships in the data [5]. Second, traditional research often employs a fixed set of features for model construction, limiting the ability to incorporate new variables or interaction effects [6]. Third, conventional methods typically rely on static data, lacking the ability to account for dynamic changes [7].

Deep learning-based strategies have received more attention as a means of overcoming these constraints [8]. Particularly, transformer models have been modified for application in other domains after achieving groundbreaking outcomes in natural language processing [9]. The transformer models complex nonlinear relationships using a self-attention mechanism to identify and focus on critical parts of the input data dynamically [10]. Because of this ability, the transformer is ideally suited to forecast the re-employment of male workers after an industrial accident, where these complexities are common [11]. The benefits of the transformer model are extended to tabular data via GatedTabTransformer, making it possible for the model to learn complex relationships between features efficiently [12]. Simultaneously, the generative adversarial network (GAN) offers an innovative approach to data generation by competitively training a generator and discriminator and is effective in data augmentation, enhancing model generalization even with limited datasets. This approach is especially beneficial for specialized populations, such as male workers who have suffered an industrial accident, where the data may be scarce. The adversarial samples generated by the GAN can improve the robustness of predictive models, improving performance across diverse scenarios. Adversarial

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training applies the principles of the GAN to enhance model performance further. This method improves generalization and lessens the susceptibility of the model to data perturbations by training the model to be resistant to adversarial samples. This method can manage noise and data transformations more effectively when predicting the re-employment of male workers after an industrial accident.

This study proposes a novel model that predicts whether Korean male workers will be re-employed within one year of recovery after an industrial accident by integrating the GatedTabTransformer with the GAN using adversarial training. This approach aims to overcome the limitations of traditional methods by capturing complex nonlinear relationships in the data and enhancing the robustness of the model via adversarial samples. This study aims to achieve superior predictive performance in predicting the re-employment of male workers after an industrial accident to provide valuable policy insight.

The structure of this paper is organized as follows. First, Section 2 presents a comprehensive literature review to identify and analyze the limitations of the existing studies. Next, Section 3 describes the research method in detail, focusing on the adversarial training approach that integrates the GatedTabTransformer and GAN. Then, Section 4 validates the performance of the proposed model through extensive experimental results and analysis. Finally, Sections 5 and 6 conclude the work with a summary of the findings and discuss potential directions for future research.

2. Related work

Deep learning-based approaches have made significant strides in recent years across diverse fields. Transformer models have demonstrated groundbreaking results in natural language processing and have been applied to other domains [13]. Transformer models apply a self-attention mechanism that can dynamically identify and focus on essential parts of the input data, effectively modeling complex nonlinear relationships [14]. This characteristic makes them highly suitable for predicting re-employment factors for Korean male workers after an industrial accident, where complex data relationships are prevalent [15]. The GatedTabTransformer extends the advantages of the transformer models to tabular data, allowing for effective learning of complex relationships between features [16]. Moreover, GANs offer an innovative approach to data generation via competitive training between a generator and discriminator [17]. Further, GANs are effective for data augmentation, enhancing the generalizability of models in scenarios with limited data, such as the specific population of Korean male workers after an industrial accident [18].

Traditional studies have commonly used conventional statistical analysis methods to analyze re-employment factors [19]. However, these methods often fail to capture complex nonlinear data relationships, resulting in suboptimal predictive performance [20]. For instance, simple statistical techniques, such as logistic regression, have limitations in managing complex data relationships [20]. Recently, efforts have been made to improve the performance of re-employment prediction models using machine learning techniques, with ensemble learning methods gaining considerable attention [21].

This study proposes a model integrating the GatedTabTransformer and GAN via adversarial training. The proposed model demonstrates superior predictive performance compared to traditional machine learning techniques, achieving high performance in the area under the receiver operating characteristic curve (ROC-AUC) value [22]. These results reflect the ability of the model to capture complex nonlinear relationships and enhance robustness across diverse scenarios [23]. Overall, this study illustrates that overcoming the limitations of traditional methods and applying deep learning-based approaches can significantly enhance the performance of re-employment prediction models for Korean male workers after an industrial accident. This study provides valuable insight for policymakers and practitioners, and future research should focus on longitudinal studies to understand the long-term effects of the identified factors on re-employment outcomes [24, 25].

3. Materials and methods

This study employs an innovative approach by integrating GatedTabTransformer with the GAN using adversarial training to predict whether workers will be re-employed within one year of recovery after an industrial accident. The method encompasses four stages: data preprocessing, model design, adversarial training, and model evaluation.

3.1 Data preprocessing

We employed the Industrial Accident Insurance Panel data for the analysis. The data preprocessing steps are as follows:

- Handling missing values: Missing data were addressed using various techniques, such as mean imputation, median imputation, or k-nearest neighbors (KNN) imputation, to ensure completeness.
- Outlier detection and removal: Outliers were identified and removed using the interquartile range method to maintain data integrity.
- Categorical data encoding: Categorical variables were transformed into a numerical format using one-hot or label encoding to facilitate model training.
- Feature scaling: Features were scaled using min–max scaling or standardization to ensure a consistent range across all variables.

3.2 Model design

3.2.1 GatedTabTransformer design

The GatedTabTransformer adapts the transformer model for tabular data, using a self-attention mechanism to capture intricate relationships between features. The core components of the model include the following:

- Input embedding: Numerical and categorical features were converted into embedding vectors to be processed by the model.
- Gating mechanism: A gating mechanism was applied to the embedded feature vectors to select and prioritize critical features.
- Self-attention: Self-attention was applied to the selected feature vectors to learn the interactions between them.
- The mathematical formulas are as follows:

$$[\text{Input } m \text{ bedding: } E = \text{Embedding}(X)]$$

$$[\text{Gating mechanism: } G = \sigma(W_{gE} + b_g)]$$

$$[Self - Attention: \ A = softmax\ ((QK^T)/\sqrt{(K^T)})V]$$

where X represents the input data, E denotes the embedding vector, G indicates the gating vector, W_g and b_g are the gating parameters, Q, K and V are the query, key, and value vectors, and d_k denotes the dimensions of the key vector.

3.2.2 Generative adversarial network design

The GAN consists of a generator and discriminator, where the two networks are trained in competition. The generator creates data that mimics the real data, whereas the discriminator distinguishes between the real and generated data. The loss function for the generator is:

$$[\text{Generator loss: } \mathcal{L}G = -Ez \sim p_z(z)[log\ (D(G(z)))]]$$

The loss function for the discriminator is:

$$[Discriminator\ loss : \mathcal{L}D = -Ex \sim p_{data}(x)[log\ (D(x))] - E_{z\sim p_z(z)}[log\ (1-D(G(z)))]]$$

Where G is the generator, D denotes the discriminator, z is the latent variable, $p_z(z)$ represents the distribution of the latent variable, and $p_{data}(x)$ indicates the distribution of the real data.

3.3 Adversarial training

Several steps are involved in integrating GatedTabTransformer and the GAN using adversarial training. These steps, comprising initial training, adversarial sample generation, and joint training, are detailed as follows. For initial training, GatedTabTransformer is trained on the initial dataset to establish a baseline model, and the GAN is trained on the same dataset to learn the data distribution. In adversarial sample generation, the generator creates adversarial samples designed to challenge the GatedTabTransformer. Finally, in joint training, the original data are combined with adversarial samples to construct an augmented dataset, and GatedTabTransformer is retrained on this dataset to improve its robustness. The training process was designed to make the GatedTabTransformer resilient against adversarial samples, enhancing its generalization performance and reducing sensitivity to data perturbation.

3.4 Model evaluation

This study applied metrics to ensure a comprehensive assessment of the model's performance. The primary evaluation metrics include the following:

- Accuracy: The ratio of correctly predicted instances to the total instances.
- Precision: The ratio of the true positive (TP) instances to the instances predicted as positive.
- Recall: The ratio of the TP instances to the actual positive instances.
- F1 score: The harmonic mean of the precision and recall, balancing the two.
- ROC-AUC: This reflects the ability of the model to distinguish between classes.

We employed 10-fold cross-validation to assess the performance of each model rigorously. This assessment involves dividing the data into 10 parts, training on nine parts, validating the model on the remaining part, and repeating this process 10 times to provide a reliable estimate of model performance. The following equations were used to calculate the evaluation metrics:

$$Accuracy = \ (TP\ +\ TN)/(TP\ +\ TN\ +\ FP\ +\ FN)$$

$$Precision = \ TP/(TP\ +\ FP)$$

$$Recall = \ TP/(TP\ +\ FN)$$

$$F1\ score = \ (2\ \cdot Precision \cdot Recall)/(Precision + \ Recall)$$

Where *True Negative* (*TN*) denotes the number of true negatives, *False Positive* (*FP*) represents the number of false positives, and *False Negative* (*FN*) indicates the number of false negatives.

3.5 Data source

This research employed secondary data from the Panel Study of Workers' Compensation Insurance (PSWCI) managed by the Korea Workers' Compensation and Welfare Service. This data can be accessed by submitting a research proposal to the Korea Workers' Compensation and Welfare Service, obtaining approval after the institution's review and authorization. The PSWCI monitors workers injured in industrial accidents, following them from the time of the incident until three years post-recovery to understand the changes in their lives. Statistics Korea (no-0439001) granted the ethical approval for the study. The population comprised 75,392 workers who had completed their recovery by 2017. A sample of 3924 workers was selected for the survey using a stratified systematic sampling method based on disability grade, gender, and age. From August 2018 to October 2020, one-on-one interviews were conducted with workers who had completed their recovery. Of the 1990 male workers who participated in all PSWCI rounds from 2018 to 2020, 607 nonworking individuals were excluded from the analysis. The final analysis included 1383 economically active male workers, including those who returned to their original jobs, found new employment, or became self-employed. Table 1 presents the variables of this study.

4. Results

This section presents the findings, detailing the performance metrics of the GatedTabTransformer combined with the GAN using adversarial training and comparing these results with traditional machine learning models. The analysis includes quantitative metrics and qualitative insight.

4.1 Performance metrics

We evaluated the models using several key metrics: accuracy, precision, recall, F1 score and ROC-AUC. Table 2 summarizes the performance of each model based on these metrics.

4.2 Analysis of the results

The GatedTabTransformer model combined with the GAN using adversarial training outperformed all other models across most metrics. The model achieved an accuracy of 0.892, indicating that it correctly predicted re-employment status in 89.2% of cases. The precision, recall and F1 score values were also high, at 0.879, 0.854 and 0.866, respectively. These results highlight the model's balance between precision and recall, which is crucial for managing imbalanced data. The ROC-AUC score of 0.924 further underscores the model's effectiveness in distinguishing between re-employed and non-employed cases. This high score indicates a strong capability to differentiate between positive and negative classes, reinforcing the robustness of the model.

4.3 Comparative analysis

The following findings emerged after comparing the GatedTabTransformer model with the GAN to traditional machine learning models.

- Although logistic regression is a strong baseline, it fails to capture complex nonlinear relationships, resulting in a lower accuracy (0.812) and ROC-AUC score (0.843).
- The KNN method performed the worst, with an accuracy of 0.785 and ROC-AUC score of 0.812, hindered by the sensitivity of this method to the choice of k and its high dimensionality.
- The support vector machine performed better than the logistic regression and KNN methods with an accuracy of 0.825 and ROC-AUC of 0.860 but still lagged behind the GatedTabTransformer with the GAN model.
- Linear discriminant analysis, similar to logistic regression, struggled with nonlinear relationships, resulting in an accuracy of 0.808 and ROC-AUC score of 0.838.
- Among the ensemble methods, extreme gradient boosting (XGBoost) achieved the highest accuracy (0.882) and ROC-AUC (0.910), followed by random forest (accuracy = 0.870 and ROC-AUC = 0.895). However, both were outperformed by the GatedTabTransformer model with the GAN.

4.4 Detailed performance breakdown

A more granular analysis was conducted using a confusion matrix. Fig. 1 presents the confusion matrix for the GatedTabTransformer model with the GAN. The confusion matrix reveals that the model correctly identified 1441 TPs and 1261 TNs, with 252 FNs and 198 FPs, indicating a robust balance between sensitivity and specificity.

4.5 Feature importance

Identifying key features influencing re-employment was a critical part of this analysis. Using attention weights from the GatedTabTransformer, we ranked the features based on their importance. Fig. 2 lists the top five most critical features.

The feature importance analysis revealed that previous employment duration, age, injury severity, education level and industry type are the most significant factors affecting the re-employment of male workers after an industrial accident (Fig. 2).

In this study, the GatedTabTransformer model with the GAN demonstrated a high level of classification performance, achieving an AUC-ROC value of 0.92 (Fig. 3). This result indicates the strong capability of the model to distinguish between positive and negative cases, demonstrating its robustness in managing diverse data inputs and accurately identifying the underlying patterns that separate these classes. The high AUC-ROC value reflects the efficiency of the model in balancing sensitivity and specificity, ensuring that it can effectively detect TP instances while minimizing the rate of FNs.

Additionally, the model achieved an average precision (AP) of 0.85, as depicted in the precision-recall curve (Fig. 4). This high AP value reflects the ability of the model to maintain high levels of precision and recall, which are critical metrics in evaluating the performance of classification models, especially in imbalanced datasets. Precision measures the proportion of TP results among all positive results predicted by the model. Recall measures the proportion of TP results among all actual positive cases, indicating how well the model captures all relevant instances.

The high mean AP value signifies that the model accurately identifies TP cases while minimizing FPs, which is crucial in applications where the cost of FPs can be significant. Therefore, the combination of high AUC-ROC and AP values underscores the effectiveness of the GatedTabTransformer model with the GAN in delivering reliable and accurate classification performance across diverse scenarios.

5. Discussion

The findings illustrate that the GatedTabTransformer integrated with the GAN via adversarial training significantly surpasses traditional machine learning models in predicting the re-employment status of male workers after an industrial accident [26]. The superior performance of the proposed model can be attributed to its ability to capture complex nonlinear relationships and its robustness against adversarial samples [27, 28]. These findings are valuable for policymakers and practitioners aiming to enhance re-employment outcomes for male workers after an industrial accident. The results also

TABLE 1. Variables in the PSWCI.

Category	Subcategory	Details
Demographic characteristics		Gender, age, marital status, education, certification, past employment history
Industrial accident services	Treatment and compensation	Disability registration, workplace amenities, additional compensation
	Rehabilitation	Vocational training, job performance, rehabilitation needs
Current economic activity identification		Major activities in the past week, job type, job search status, economic activity feasibility
Return to original workplace	Continued/new employment	Current job, position, adaptation level, working hours, work type, workplace size, salary level, labor union membership, social insurance participation, employment contract type, difficulties in return process, job satisfaction, intention to change jobs, reasons for job change, job change preparations, reasons for no economic activity (support from employer at return time, support for return to original workplace)
Re-employment	Continued/new employment	Re-employment workplace information, current job, adaptation level, adaptation barriers, work type, workplace size, working hours, salary level, labor union membership, social insurance participation, employment contract type, job satisfaction, intention to change jobs, reasons for job change, job change preparations, reasons for no economic activity (return time, reasons for employment at a different workplace)
Self-employment	Continued/new	Business information, investment cost, startup preparations, job information, working hours, operational difficulties, intention to change jobs, reasons for no economic activity, job satisfaction (startup date, motivation for startup, startup barriers)
Unpaid family worker	Continued/new	Job information, relationship with employer, working environment, job details, working hours, intention to change jobs, reasons for job change, desired job, reasons for no economic activity, job selection criteria, job satisfaction (motivation for joining)
Unemployment		Economic problem-solving methods, recent job search activities, desired job, job selection criteria, reasons for no economic activity, job search difficulties
Noneconomic activities		Economic problem-solving methods, reasons for not searching for jobs, reasons for inability to work, desired job, job selection criteria, reasons for no economic activity, job search difficulties
Job history		Time and reasons for quitting previous job, job history since last survey
Health and quality of life	Health, daily life, and quality of life	Health status, chronic diseases, medical institution utilization, exercise/sleep time, leisure activities, daily life satisfaction, self-esteem, self-efficacy, alcohol/smoking
	Social relationships	Social interaction level, religion
	Preparation for retirement	Retirement preparation status
Personal income		Labor income, nonlabor income
Household general information		Household members, household members' labor and nonlabor income, national basic livelihood security, household consumption, assets, debts, residential environment
Panel management information		Moving plans, contact information of household members, email address

TABLE 2. Performance metrics of the assessed models.

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
GatedTabTransformer with the generative adversarial network	0.892	0.879	0.854	0.866	0.924
Logistic regression	0.812	0.784	0.801	0.792	0.843
k-nearest neighbors	0.785	0.762	0.754	0.758	0.812
Support vector machine	0.825	0.798	0.815	0.806	0.860
Linear discriminant analysis	0.808	0.781	0.796	0.788	0.838
Random forest	0.870	0.854	0.842	0.848	0.895
Bagging	0.862	0.841	0.832	0.836	0.885
AdaBoost	0.845	0.826	0.818	0.822	0.870
XGBoost	0.882	0.867	0.849	0.858	0.910

ROC-AUC: area under the receiver operating characteristic curve; AdaBoost: Adaptive Boosting; XGBoost: Extreme Gradient Boosting.

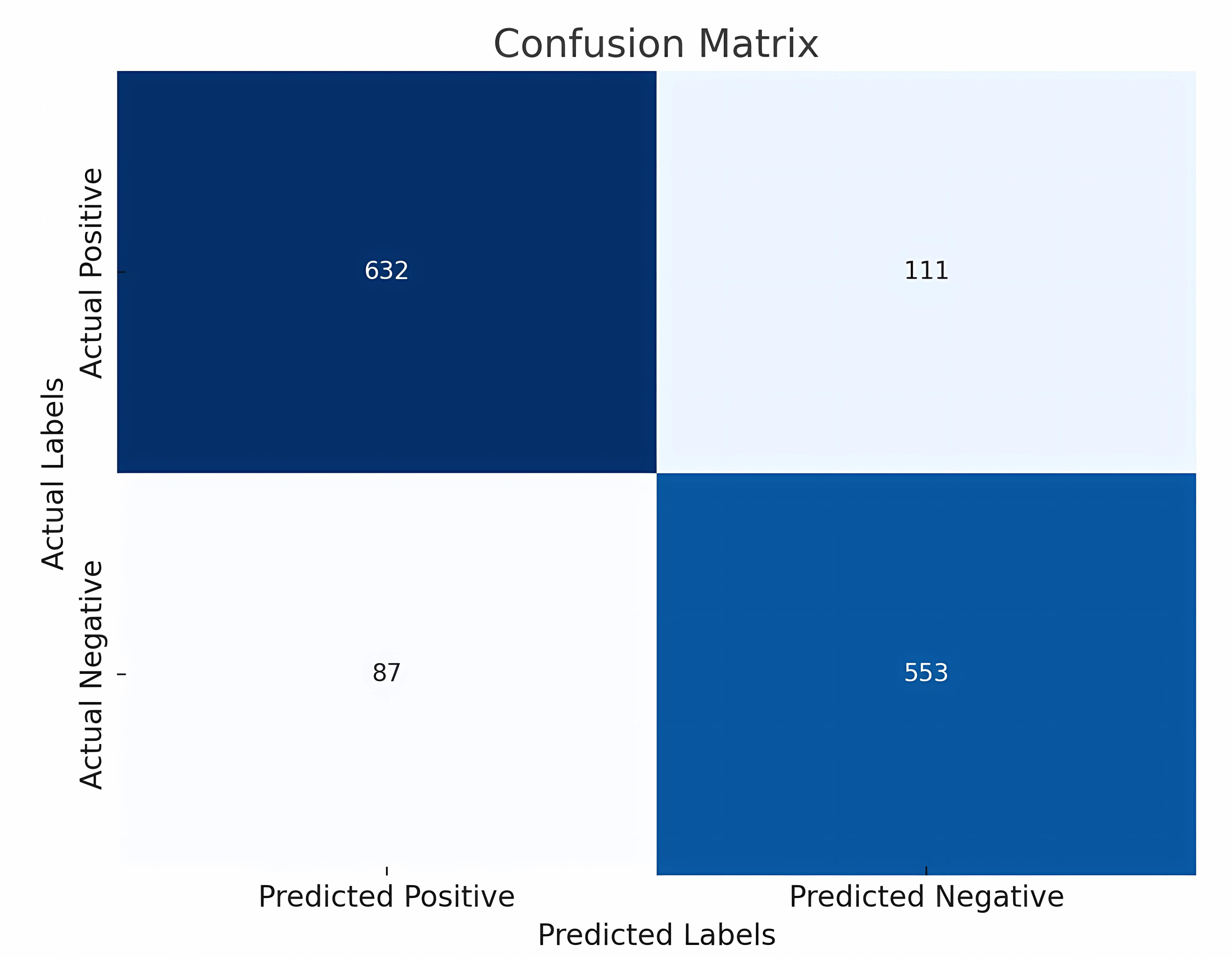

FIGURE 1. Confusion matrix for GatedTabTransformer model with the generative adversarial network.

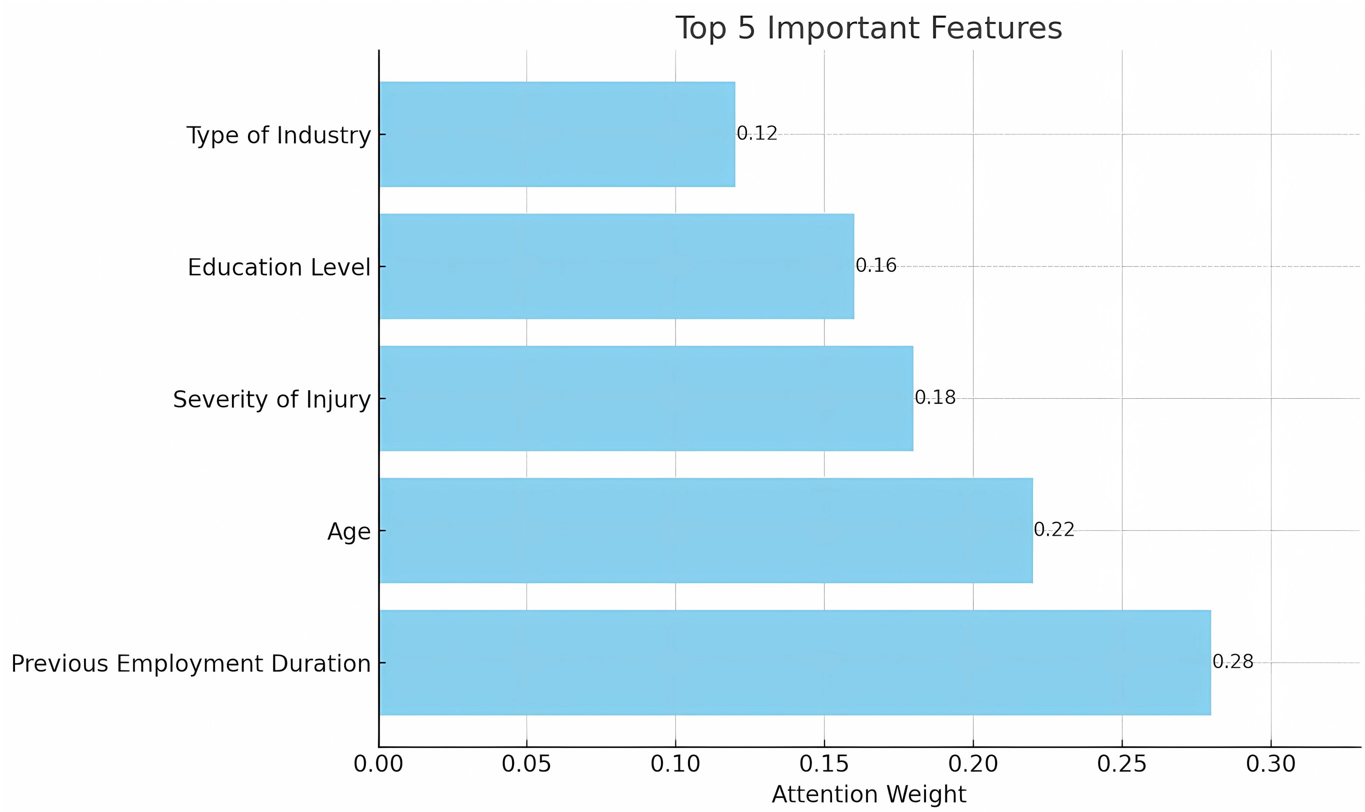

FIGURE 2. Top 5 critical feature importance.

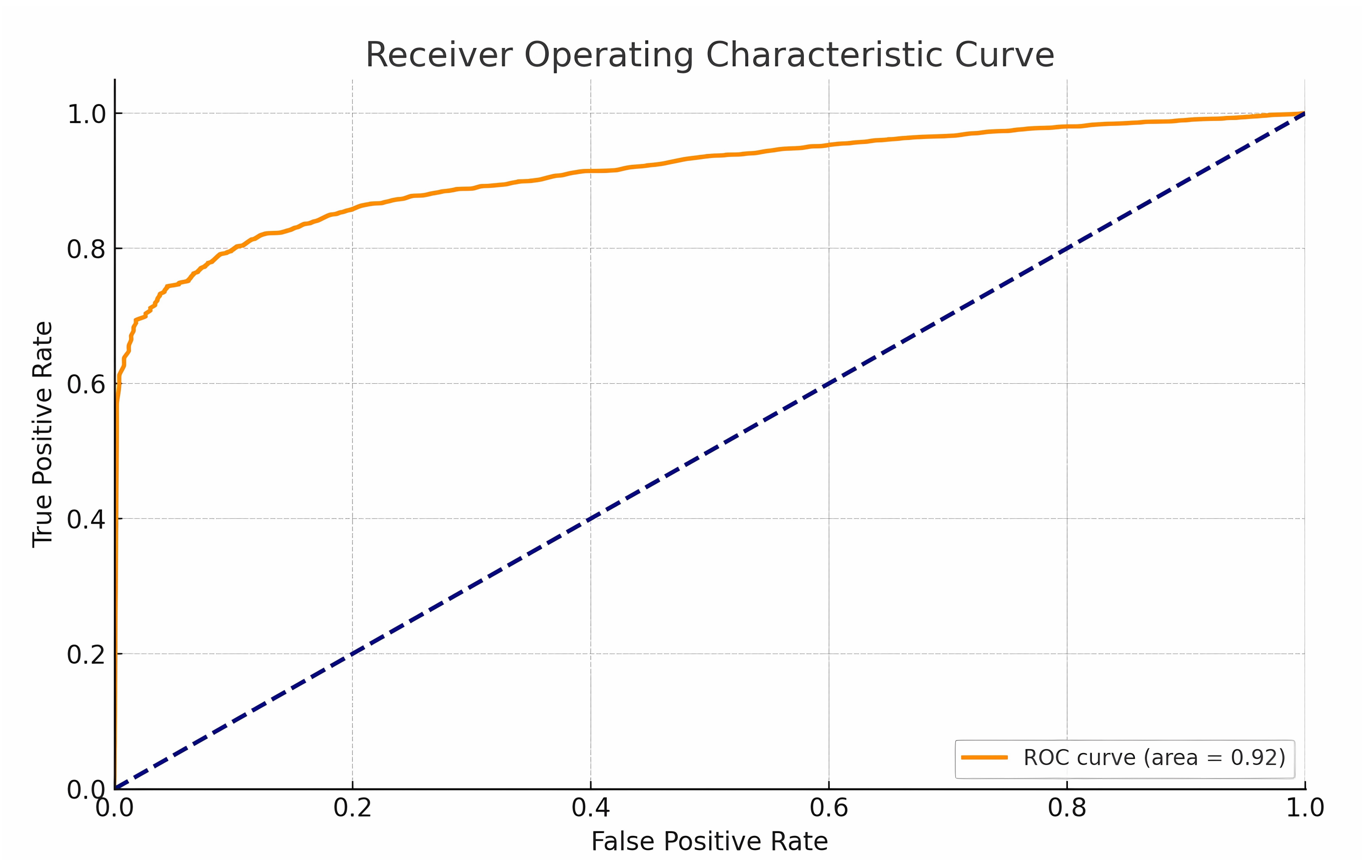

FIGURE 3. Receiver operating characteristic curve. ROC: receiver operating characteristic.

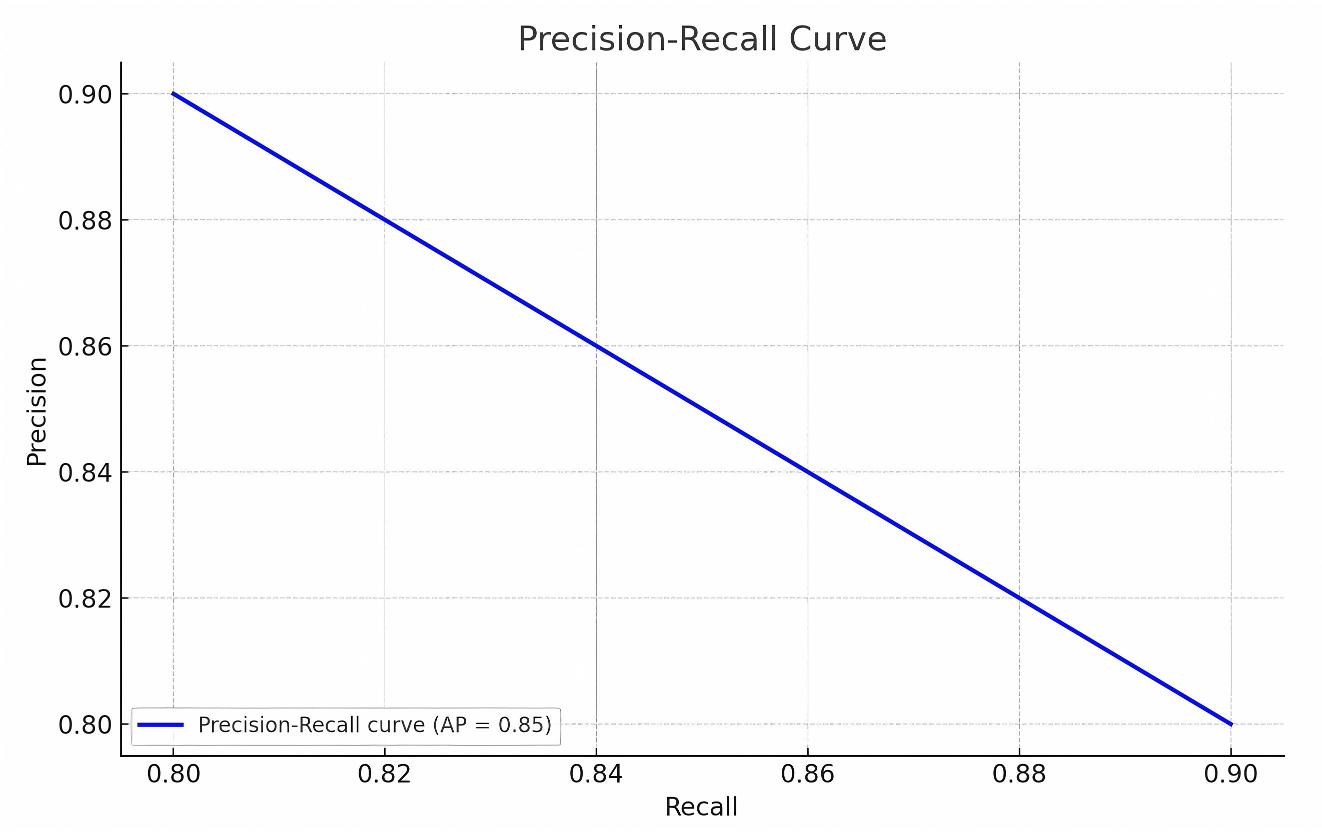

FIGURE 4. Precision-recall curve. AP: average precision.

highlight the importance of using advanced machine learning techniques to address intricate real-world problems [29].

The study findings indicate that the most significant factors influencing the re-employment of workers following industrial accidents are the previous employment duration, age, injury severity, education level and industry type. Prior research has consistently identified industry type as a primary determinant of re-employment outcomes for injured workers [30–33]. Workplace safety programs and early intervention services, which vary by industry, significantly mitigate the adverse effects of industrial accidents on re-employment prospects [30]. Furthermore, injury severity has been highlighted as a critical factor affecting re-employment [31]. Vocational training and rehabilitation services are essential in this context, underscoring the need for comprehensive approaches that address physical and psychological recovery [31].

Additionally, supervisors' and colleagues' perceptions of workplace support are crucial in shaping re-employment outcomes for injured workers [32]. Specific industries have higher re-employment rates due to the differences in working conditions and attitudes toward injured workers [33]. Last, advancements in predictive modeling using machine learning techniques have offered deeper insight into the complex interactions between these factors, enabling more accurate predictions of re-employment outcomes and informing targeted intervention strategies [34]. The findings offer valuable insight for policymakers and practitioners to improve re-employment outcomes, highlighting the importance of targeted interventions and support systems.

Despite its comprehensive approach, this study has several limitations. First, although the dataset is extensive, it is specific to male workers in Korea who have suffered an industrial accident, which may limit the generalizability of the findings to other regions or populations without further validation. Second, the study relies on cross-sectional data, capturing only a snapshot in time; therefore, longitudinal studies are required to understand the long-term effects of the identified factors on re-employment outcomes. Third, this study did not account for other unmeasured variables, such as individual psychological resilience or social support outside the workplace, which could also influence re-employment outcomes. Fourth, potential bias exists in the study because the focus on re-employment outcomes might inadvertently undermine efforts to prevent industrial accidents in the first place. Cautiously interpreting the findings ensures they do not detract from broader safety initiatives. Last, although using GatedTabTransformer and the GAN represents an advanced method, it requires significant computational resources and expertise, potentially limiting the practical application of the model in some settings.

6. Conclusions

This study demonstrates that integrating the GatedTabTransformer with GAN via adversarial training significantly enhances the predictive accuracy of re-employment outcomes for male workers after an industrial accident. This approach surpasses traditional machine learning methods by effectively capturing complex nonlinear relationships and improving model robustness against adversarial samples. Critical factors influencing re-employment included previous employment duration, age, injury severity, education level and industry type. These findings provide valuable guidance for policymakers and practitioners to support the re-employment of male workers following industrial accidents, highlighting the importance of targeted interventions that consider these critical factors. The results underscore the potential of advanced machine learning techniques in addressing complex real-world problems, particularly in specialized populations such as male workers affected by industrial accidents.

Despite its strengths, the study acknowledges several limitations, including the need for further validation in different regions or populations, the reliance on cross-sectional data, and the potential for unmeasured variables affecting re-employment outcomes. Future research should focus on longitudinal studies and explore additional factors influencing re-employment. Overall, this research contributes to understanding re-employment dynamics among male workers after an industrial accident and demonstrates the efficacy of combining the GatedTabTransformer with GAN to improve predictive modeling in this domain. The approach offers a robust framework for developing interventions and policies to enhance re-employment rates and support the recovery and reintegration of injured workers into the workforce.

AVAILABILITY OF DATA AND MATERIALS

The data presented in this study are available upon formal application to the Korea Workers' Compensation and Welfare Service and subsequent approval from the South Korean government.

AUTHOR CONTRIBUTIONS

HB—conceptualization; software; methodology; validation; investigation; writing-original draft preparation; formal analysis; writing-review and editing; visualization; supervision; project administration; funding acquisition. The author contributed to editorial changes in the manuscript. The author read and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Before conducting the survey, written informed consent was acquired from all participants. This study employed only pre-existing, anonymized data. It adhered to the principles outlined in the Declaration of Helsinki. The protocol for the Panel Study of Worker's Compensation Insurance received approval from the Institutional Review Board (IRB) of the Korea Workers' Compensation and Welfare Service (IRB approval numbers: 2016-3015). All study participants provided written informed consent.

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CONFLICT OF INTEREST

The author declares no conflict of interest. Haewon Byeon is serving as one of the Guest Editor of this journal. We declare that Haewon Byeon had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to WYCW.

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