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Article

DYNAMIC UNCERTAINTY-AWARE BAYESIAN NEURAL MODEL FOR REAL-TIME WORKFORCE DISPLACEMENT RISK UNDER AI AUTOMATION

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Abstract: The growing adoption of artificial intelligence (AI) in the workplace requires moving workforce displacement prediction in real-time and with uncertainty. This paper presents a probabilistic deep learning system that combines Bayesian Neural Nets (BNN) with Deterministic Deep Neural Networks (DNN), Monte Carlo (MC) Dropout, and a hybrid ensemble architecture to perform task-level displacement prediction. Empirical testing of 18,796 standardized task-level data indicates that all models converge to the same place, with BNN Gaussian NLL converging to -0.94 and MSE converging to approximately 0.056. The Bayesian model produced better results with a MSE = 0.0558, RMSE = 0.2361, MAE = 0.1902, and R 2 = 0.0670, whereas the Hybrid model marginally increased the results (MSE = 0.0556, R 2 = 0.0691). Calibrated probabilistic forecasting was confirmed based on the diagnostic analysis of heteroscedastic residual patterns and positive correlation between predictive uncertainty and absolute error. The error in the segmentation in terms of classes was the lowest in the Medium-risk occupations and the highest in the High-risk groups. The framework will be useful in uncertainty-sensitive and dynamic displacement predictions under AI-based labor transformation.

Keywords: Bayesian Neural Networks; Workforce Displacement; AI Automation; Uncertainty Quantification; Labor Market Forecasting

1. INTRODUCTION

The idea of artificial intelligence (AI) and automation technologies is fast changing the labor market in many countries of the world and raising the tension regarding the concept of job displacement, restructuring of the workforce, and economic inequality. In contrast to previous mechanization cycles, when most of the work included in routine and manual work was outsourced, modern AI applications are increasingly taking the role of cognitive processes, analysis, and decision-making, which are traditionally linked to human professionalism. Consequently, the range of jobs at risk of automation has grown not only to less-skilled positions, but also to professional and knowledge-based ones [1]. The empirical data indicate that AI implementation is a source of job displacement and job creation at the same time, but with significant discrepancies in its impact on occupations, industries, and skills [2]. This heterogeneity poses a challenge to traditional methods of labor market forecasting that are based on unvarying assumptions and deterministic forecasts. The framework in Figure 1 combines the dynamics of AI adoption and labor market heterogeneity through a Bayesian neural architecture to provide real-time risk assessment of workforce displacement dynamically by way of uncertainty.

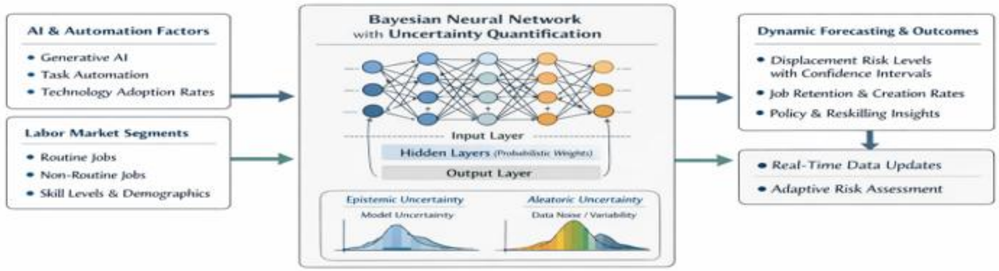

Figure 1: A Dynamic Uncertainty-Aware Bayesian Neural Model for Workforce Displacement Risk Under AI Automation.

Figure 1: Uncertainty-Aware Bayesian Model for Workforce Displacement Risk

The recent innovation in machine learning and generative AI has made the automation of non-routine activities, such as language processing and data analysis (as well as complex problem solving), even more important. New research indicates that non-routine occupations can be just as susceptible to automation as routine occupations, and previous beliefs that cognitive jobs are somewhat resistant to technological replacement are being reversed [3]. Specifically, the risk of displacement of highly skilled professionals, who deal with analytical and information-intensive tasks, is on the rise, and the shortcomings of occupation-level measures of exposure and the relevance of task-level analytical models are highlighted [4]. These results show that automation risk is not well represented only with static occupational classifications. One of the key obstacles to predicting AI-driven labor market displacement is the fact that it is difficult to predict the uncertainty of labor market reactions. The nature of employment results is determined by multilateral factors between technological diffusion and organizational strategies, policy interventions, and macroeconomic conditions. However, most current econometric and machine learning frameworks are based on point estimates that are made using historical data, which do not give good information on how trustworthy their predictions are [5]. Projections that do not explicitly indicate uncertainty have limited usefulness to policy makers and labour planners, especially when the adoption of AI is not evenly distributed across the sectors, regions, and demographics.

Bayesian machine learning can be used to overcome these shortcomings by working with models of predictions as probability distributions instead of fixed values. Bayesian neural networks are an extension of traditional neural networks, which probabilistically incorporate the network parameters and approximate the posterior distribution when new data is received [6]. In this way, it is possible to explicitly quantify epistemic uncertainty due to a lack of knowledge and aleatoric uncertainty that expresses inherent variations in the labor market [7]. These probabilistic representations are particularly appropriate when dealing with a dynamic environment with high rates of technological change and constantly changing streams of data [8]. Although Bayesian deep learning and uncertainty quantification have advanced, their use in forecasting the displacement of the workforce has not been extensively explored. The current simulation is based on a lot of literature, which depends on the regression models, which are not dynamic, or the exposure indices of automation, which are not probabilistic and cannot be adjusted in real time [9]. Empirical research also indicates that there is a high level of heterogeneity in the effects of AI among different population groups, education, and work types [10], which requires the development of adaptive models. Dynamic Bayesian inference can be used to update predictions sequentially as new data arise [11], whereas perception-based analyses reveal varied reactions of workers to the threat of automation [12]. Wider economic studies propose that the use of AI can strengthen inequality [13], despite the creation of complementary AI-human skills demands [14]. It is also proven that non-routine, highly skilled jobs are under pressure from automation and contribute to the significance of uncertainty-conscious task-based evaluation models [15].

Even though the previous research has contributed to the deep comprehension of the displacement of workers with the help of AI, it is rather based on unchanging and linear models that fail to measure the uncertainty in predictions and cannot respond to labor market dynamics. There is a limited number of task-level, uncertainty-sensitive, and dynamically changing frameworks. In order to fill this gap, this study aims to develop a Dynamic Uncertainty-Aware Bayesian Neural Model that would predict the risk of workforce displacement in real time during AI automation. The suggested methodology will focus on displacement-risk estimation on a task and occupation level, quantify and explicitly estimate uncertainty with the help of Bayesian inference, and constantly update predictions as data on labor and AI adoption availability becomes available, thus helping to make informed workforce planning, reskilling plans, and evidence-based policy decisions.

2. RELATED WORK

The issue of AI-based workforce displacement has already been researched widely, focusing on task-based vulnerability, labor market adjustment, and policy inferences. Xu et al. (2025) [16] produced a BERT-based model to assess the automatability of tasks at the task level to demonstrate that routine and semi-routine tasks pose the greatest risk. They, however, failed to tackle the issue of time dynamics and uncertainty in their model, hence restricting its application to real-time assessment of labor risk. An auditing study with the use of the WORKBank dataset was performed by Shao et al. (2025) [17], who tried to discuss the preferences of workers regarding AI automation and found the discrepancy between human expectations and AI capabilities. Although thought-provoking, the study did not capture real-time predictive modeling that is essential in adaptive workforce planning. Occhipinti et al. (2024) [18] evaluated the risk that generative AI is going to intensify the labor market disruptors, but did not estimate the risk probabilities as macroeconomic impacts. On the same note, Sy (2025) [19] also evaluated the dual role of AI in employment and emphasized the necessity of adaptive policies, but their framework was deterministic and fixed to time, instead of responding to the changes in the labour market. The work models of Constantinides et al. (2025) [20] suggested the idea of blending human and AI working environments, which may provide transparency and accountability, but quantitative predictions of the risk of displacement were not offered.

Recent research also indicates that dynamic and uncertainty-sensitive solutions are necessary. A comparative study of skill-based polarization of the labor market discovered by Ganuthula and Balaraman (2025) [21] indicates that there is increased automation risk in the low-skill-intensive economies. A framework of the labor market shock due to new technologies was created by Fan (2025) [22], which examined the concentration of automation and AI in skills and its impact on wages and mobility. In a study of automation and augmentation AI, Marguerit (2025) [23] concluded different effects between low and high-skilled jobs. A startup-based AI exposure index (AISE) to quantify occupational AI exposure has been proposed by Fenoaltea et al. (2024) [24], which is more precise than theoretical measures of AI adoption. An AI-based study of the workforce research carried out by Samatova et al. (2025) [25] recognized trends in automation risk and the need to reskill. Despite the fact that these studies contribute to the literature on the impact of AI on labor, they do not include the real-time prediction involving uncertainty quantification, which restricts the taking of action.

In order to fill these gaps, this research presents a Dynamic Uncertainty-Aware Bayesian Neural Model (DUA-BNM). The model that is developed combines task-level analysis, time update, and probabilistic prediction, which enables real-time evaluation of the risk of displacing the workforce. As opposed to the previous literature, DUA-BNM measures expected risk and predictive uncertainty, and thus, allows policymakers and organizations to detect high-risk jobs dynamically and act on them as well as invest in reskilling, job redesign, and specific policy actions. This study fills the gap in deterministic forecasting of specific tasks with probabilistic forecasting of risks in real-time by automating workforce planning to offer a solid framework that can be applied in practical workforce planning in the context of AI automation.

3. RESEARCH METHODOLOGY

The research design of the given study aims at generating a Dynamic Uncertainty-Aware Bayesian Neural Model (DUA-BNM) to forecast the risk of real-time workforce displacement in the event of AI automation. It starts with an in-depth data collection and preprocessing, feature extraction at the task level, probabilistic modeling based on Bayesian neural networks, and dynamic updating of features to make real-time predictions, and finally, the evaluation and verification.

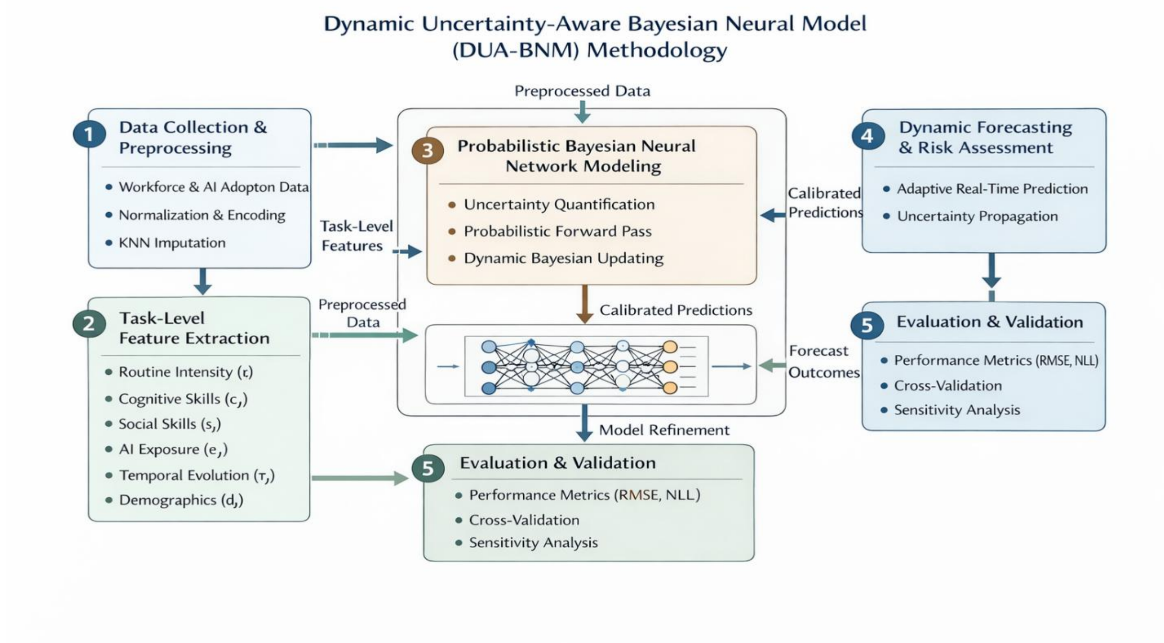

Figure 2: Methodological Framework of the Proposed DUA-BNM Model

The methodological workflow of the proposed DUA-BNM framework is described in Figure 2, and it includes data preprocessing, task-level feature extraction, Bayesian neural network modeling, dynamic real-time updating, and evaluation steps, which, together, allow making uncertainty-aware predictions of the risk of workforce displacement when AI is used.

3.1 Data Collection and Preprocessing

Workforce and AI adoption data were obtained from occupational surveys, industry AI adoption reports, and startup-based AI exposure indices. Each occupation $o_i$consists of multiple tasks t_j, represented as feature vectors. Continuous variables such as task frequency and AI exposure scores were normalized using min–max scaling:

$$x_{ij}^{\text{scaled}} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

One-hot encoding was used to encode categorical variables. The K-nearest neighbors (KNN) method was used to provide the missing values. The consistency between task-level and occupation-level data was established through temporal alignment across several years.

3.2 Task-Level Feature Extraction

Each task $t_j$within an occupation $o_i$is represented by a feature vector:

$$\mathrm{x}_{ij} = [r_j, c_j, s_j, e_j, \tau_j, d_j]$$

where $r_j$denotes routine intensity, $c_j$represents cognitive skill requirements, $s_j$captures social skill intensity, e_j corresponds to AI exposure, τ_j represents temporal evolution, and d_j includes demographic or socio-economic factors. These features collectively capture intrinsic task properties and contextual influences, enabling assessment of heterogeneous vulnerability to AI automation.

The temporal evolution of task characteristics is modeled using a weighted moving average:

$$\tau_j(t) = \frac{\sum_{k=0}^{n} e^{-\lambda k}\, x_j(t-k)}{\sum_{k=0}^{n} e^{-\lambda k}}$$

where λ is a decay parameter assigning greater weight to recent observations. This formulation ensures that recent changes in task composition and AI adoption exert a stronger influence on displacement risk.

Occupational displacement risk is aggregated from task-level predictions as:

$$R_i = 1 - \prod_{j=1}^{T_i} (1 - \hat{y}_{ij})$$

where $\hat{y}_{ij}$ is the predicted displacement probability for the task j, and T_i denotes the total number of tasks in the occupation o_i. This multiplicative aggregation captures the cumulative impact of multiple automatable tasks, with task interactions implicitly modeled through the Bayesian neural network.

3.3 Bayesian Neural Network Modeling

The Bayesian Neural Network (BNN) is the main part of the DUA-BNM model. Contrary to deterministic neural networks, BNNs produce probabilistic forecasts and explicitly estimate the uncertainty, which is essential in assessing the risk of displacing the workforce due to the automation of AI-driven processes.

3.3.1 Probabilistic Framework

In a BNN, network weights Ware treated as random variables. Given task features Xand observed outcomes y, the posterior distribution over weights is defined as:

$$p(\mathrm{W} \mid \mathrm{X}, \mathrm{y}) \propto p(\mathrm{y} \mid \mathrm{X}, \mathrm{W})\, p(\mathrm{W})$$

Since exact posterior inference is intractable, variational inference is employed to approximate the posterior with a parametric distribution. $q_\theta(\mathrm{W})$, allowing the model to capture epistemic uncertainty.

3.3.2 Forward Pass and Predictive Output

The forward propagation in a BNN follows the same structural form as a standard neural network, but incorporates probabilistic weights:

$$\mathrm{h}^{(l)} = f\left(\mathrm{W}^{(l)}\mathrm{h}^{(l-1)} + \mathrm{b}^{(l)}\right)$$

For each task t_j, the network outputs a probabilistic displacement prediction:

$$\hat{y}_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$$

where μ_j is the predictive mean and σ_j^2 represents total predictive uncertainty, capturing both aleatoric uncertainty (data noise) and epistemic uncertainty (model confidence).

3.3.3 Loss Function and Training

Training of the BNN is performed by minimizing a loss function that balances data fit and regularization:

$$\mathcal{L} = -\sum_{i=1}^{N} \log \mathcal{N}(y_i \mid \mu_i, \sigma_i^2) + \beta \sum_{l} \mathrm{KL}\left(q_\theta(\mathrm{W}^{(l)}) \parallel p(\mathrm{W}^{(l)})\right)$$

The KL divergence term penalizes prediction deviation, and the first term makes sure the predictions are accurate as well. The algorithm can enable the BNN to offer uncertainty-aware real-time displacement forecasts that can be used in AI automation to plan the workforce.

3.4 Dynamic Updating and Real-Time Forecasting

The Bayesian framework enables continuous updating as new data arrive:

$$p(\mathrm{W} \mid \mathrm{X}_{1:t+1}, \mathrm{y}_{1:t+1}) \propto p(\mathrm{y}_{t+1} \mid \mathrm{X}_{t+1}, \mathrm{W})\, p(\mathrm{W} \mid \mathrm{X}_{1:t}, \mathrm{y}_{1:t})$$

To ensure stable yet responsive predictions, task-level displacement probabilities are smoothed using exponential weighting:

$$\hat{y}_j(t+1) = \alpha \hat{y}_j(t) + (1-\alpha)\hat{y}_j^{\mathrm{new}}, 0 < \alpha < 1$$

It can quickly adjust to the new trends of AI or unexpected changes in the labor market and preserve the temporal stability in that way. Estimates of occupational risk are brought up-to-date using the previously defined aggregation function, and temporal embeddings are also used to increase the sense of responsiveness to changing patterns.

3.5 Model Evaluation and Validation

Model performance is assessed using Root Mean Squared Error (RMSE), Negative Log-Likelihood (NLL), and coverage probability to evaluate uncertainty calibration:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$

$$\mathrm{NLL} = -\sum_{i=1}^{N}\log p(y_i \mid \mathrm{x}_i)$$

$$\mathrm{Coverage} = \frac{1}{N}\sum_{i=1}^{N} 1\{y_i \in [\mu_i - 1.96\sigma_i, \mu_i + 1.96\sigma_i]\}$$

The sensitivity analysis involves the change or perturbation of the important input characteristics, and it monitors the change in the forecasted displacement risk. The cross-validation in diverse industries and over time division guarantees the strength and generalization. In general, this approach provides real-time, uncertainty-aware, task- and occupation-level workforce displacement forecasting to help inform reskilling and workforce adaptation policies.

4. RESULTS AND DISCUSSION

The experimental analysis explores predictive behaviour, uncertainty modelling ability and comparative robustness of deterministic, probabilistic and ensemble architectures in real-time displacement forecasting in the workforce when automated by AI. All models received a personalized and consistent training-testing framework and were trained on the standardized features of the workforce on the task level and AI exposure indicators. The aspect of performance was studied in terms of convergence stability, diagnostic analysis, uncertainty calibration, and class-wise error distribution, as well as the overall regression measures. Results are provided in the following subsections in a logical sequence, such as training stability, uncertainty-aware modeling, comparative evaluation, ensemble integration, and risk-level segmentation.

4.1 Model Convergence and Training Stability Analysis

It is imperative to measure the extent to which every model is convergent in terms of training before analyzing the predictive reliability. Convergence behavior indicates stability of optimization, generalization ability, and efficiency of learning. Deterministic, stochastic, and fully probabilistic models were trained using the same data preprocessing and splitting. The training and validation loss per epoch is monitored to give an insight into overfitting control, stability of parameters, and optimization balance.

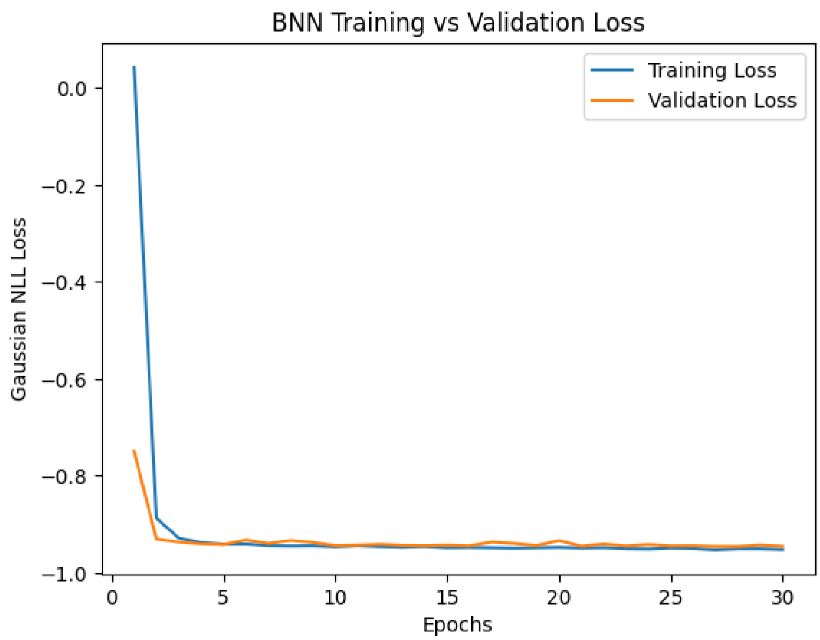

Figure 3: Training and Validation Gaussian NLL Loss Curve of the Bayesian Neural Network (BNN)

Figure 3 depicts the training and validation Gaussian Negative Loss (NLL) of the Bayesian Neural Network with 30 epochs. First, there is a steep drop in the training loss, which means that the parameters can adjust quickly and converge effectively in the initial stages of learning. The loss in validation has a similar decreasing trend, which is highly consistent with the training curve following the initial several epochs. The curves being stabilized at about -.94 indicate convergence of the models and the optimization of the models being stable. The small gap between the training and validation losses indicates no serious overfitting. Negative NLL values should be present in probabilistic modeling, which affirms successful uncertainty-aware learning in the Bayesian model.

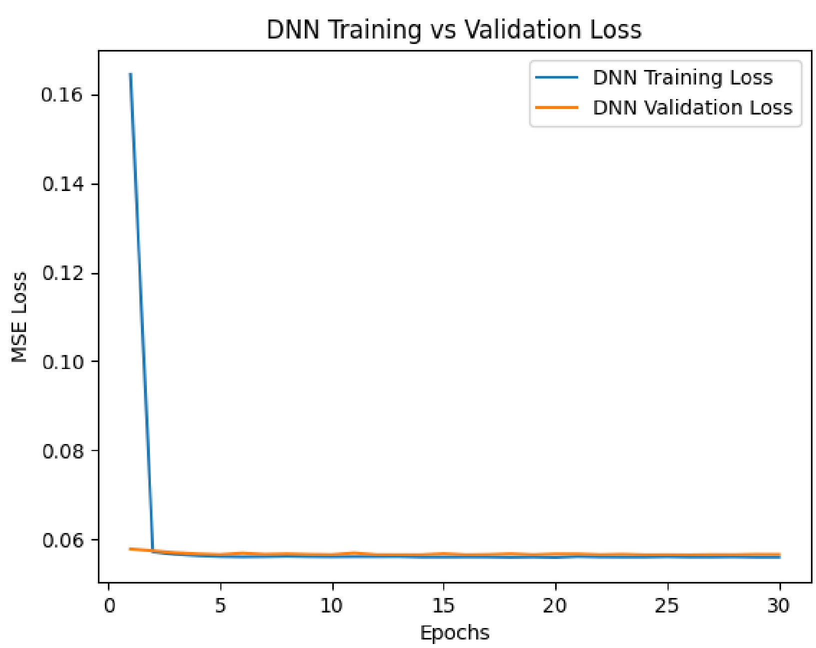

Figure 4: Training and Validation MSE Loss Curve of the Deterministic Deep Neural Network (DNN)

Figure 4 demonstrates the value of the training and validation Mean Squared Error (MSE) loss of the Deterministic Deep Neural Network per 30 epochs. First, the training loss has a steep decrease to a large value, meaning that there is rapid learning and efficient parameter adjustment at the initial iterations. Both training and validation losses level off to about 0.056, which shows that the model has converged after the initial few epochs. The fact that the two curves are very similar implies that there is little overfitting, and the performance of generalizing is high. The trend is smooth and consistent, which means that optimization is stable, which fact proves that DNN can provide predictive results that are reliable when it comes to the estimation of the risk of workforce displacement.

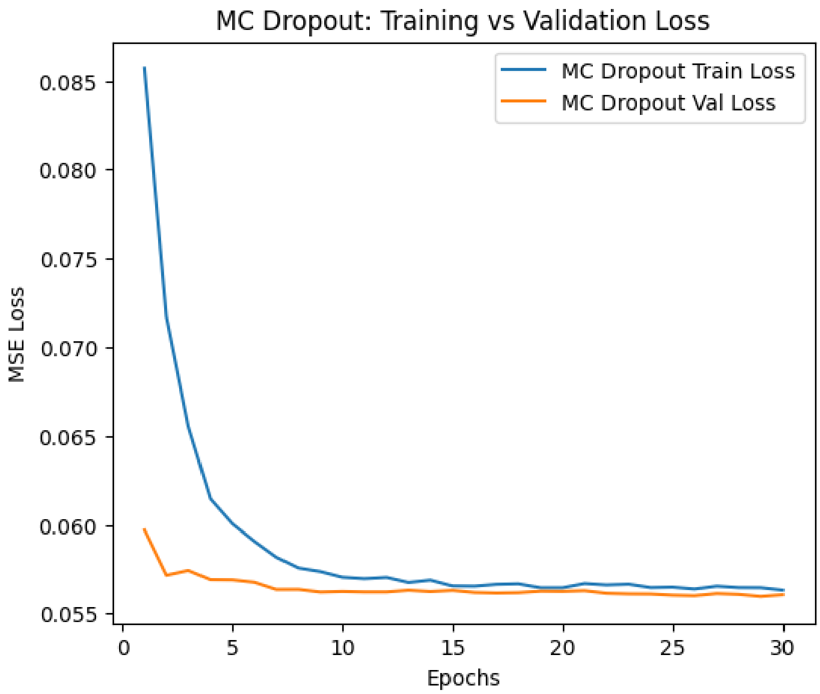

Figure 5: Training and Validation MSE Loss Curve of the Monte Carlo (MC) Dropout Neural Network

Figure 5 shows the training and validation Mean Squared Error (MSE) loss of the MC Dropout Neural Network in 30 epochs. The loss in the training process begins declining steeply at the very beginning, which means that the learning is quick in the initial iterations. The training and validation losses stabilize at about 0.056 after a number of 8-10 epochs, which indicates convergence of the model. The fact that the two curves are very close implies that there is little overfitting and that there is a high degree of generalization. Minor changes in training loss are an indicator of the stochasticity of dropout regularization. In general, the convergence pattern is stable, which is an indicator of effective learning and maintenance of uncertainty estimation with the Monte Carlo sampling.

On the whole, there is stable convergence and optimisation in all models. Nevertheless, only the probabilistic formulation allows predictive learning, as well as converging to uncertain goals. The next part measures detailed diagnostic and uncertainty behavior.

4.2 Predictive Performance and Uncertainty Analysis of the Bayesian Neural Network

Other than convergence, the strength of the probabilistic model is that it can be used to measure predictive uncertainty and estimate displacement risk. The Bayesian Neural Network is able to produce predictive mean and variance on every observation, enabling one to judge calibration, residual behavior, and uncertainty dispersion. Diagnostic imaging facilitates the greater evaluation of predictive credibility and uncertainty design.

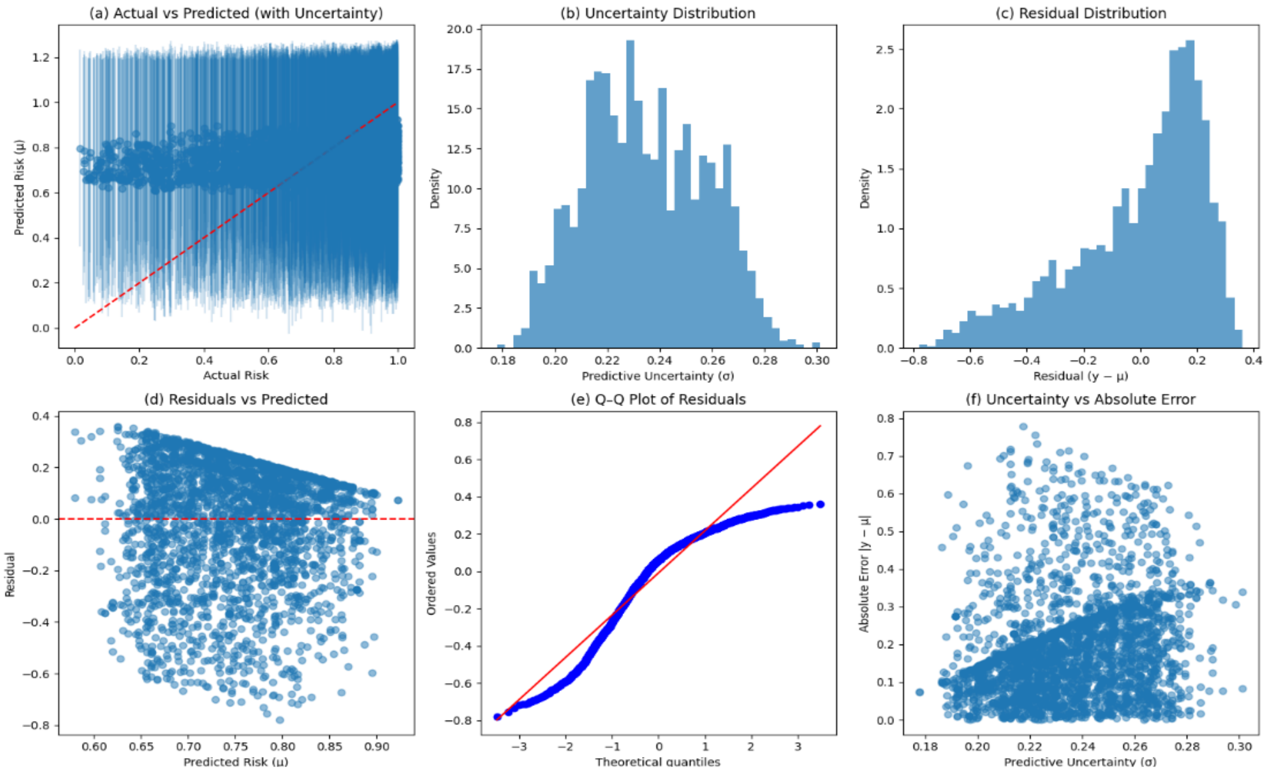

Figure 6: Diagnostic and Uncertainty Analysis of the Bayesian Neural Network (BNN) for Workforce Displacement Prediction

The actual and predicted values with uncertainty bands are displayed in Figure 6(a), with the visible deviations around the optimal diagonal line implying that the predictive ability and variability in estimating the displacement risks are moderate. Figure 6(b) shows the uncertainty distribution, which has a rather wide distribution of predictive standard deviations, representing epistemic uncertainty that is represented by the Bayesian model. Figure 6(c) shows the distribution of the residual, which is asymmetric and widely distributed; that is, there are unequal prediction errors. Figure 6(d) shows predicted values against the residuals, and it indicates heteroscedastic trends and clustered values. Figure 6(e) illustrates the Q-Q plot indicating non-normal behavior of residuals. Fig 6(f) shows there is a positive correlation between uncertainty and absolute error.

The attained consistency between the uncertainty and error validates the calibrated probabilistic forecast and proves the flexibility of the model to the heterogeneous variability of labor markets. The following subsection is a comparison of these results with deterministic and approximate Bayesian approaches.

4.3 Comparative Diagnostic Evaluation of Deterministic and MC Dropout Models

In order to be able to see structural variations between modeling approaches, the diagnostic performance of both deterministic and MC Dropout architectures was tested at the same set of experimental conditions. These comparisons point to the differences in predictive dispersion, predictive residual structure, and representation of uncertainty.

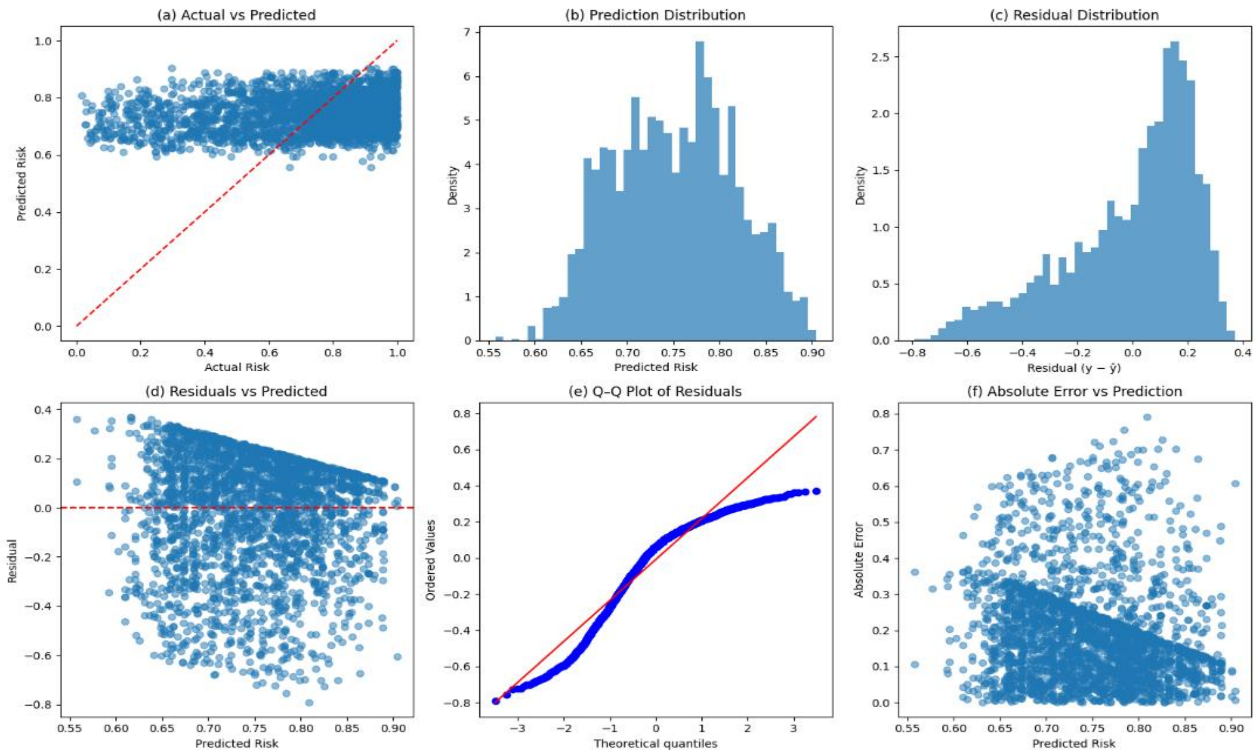

Figure 7: Diagnostic Analysis of the Deterministic Deep Neural Network (DNN) for Workforce Displacement Prediction

In Figure 7(a), the Actual vs Predicted plot depicts that there is significant scatter around the straight line, and this indicates a moderate predictive power. The prediction distribution in Figure 7(b) shows that there is a concentration in a thin range of risk, meaning the variability of output is little. Figure 7(c) shows the distribution of residuals, which is asymmetric and widely distributed, showing uneven prediction errors. Figure 7(d) illustrates the results of the residual versus predicted values with heteroscedastic behavior and patterns of systematic error. The Q-Q plot is shown in Figure 7(e); the deviation from the reference line shows non-normal residuals. Figure 7(f) illustrates an absolute error versus prediction that indicates that different risk levels have different error magnitudes.

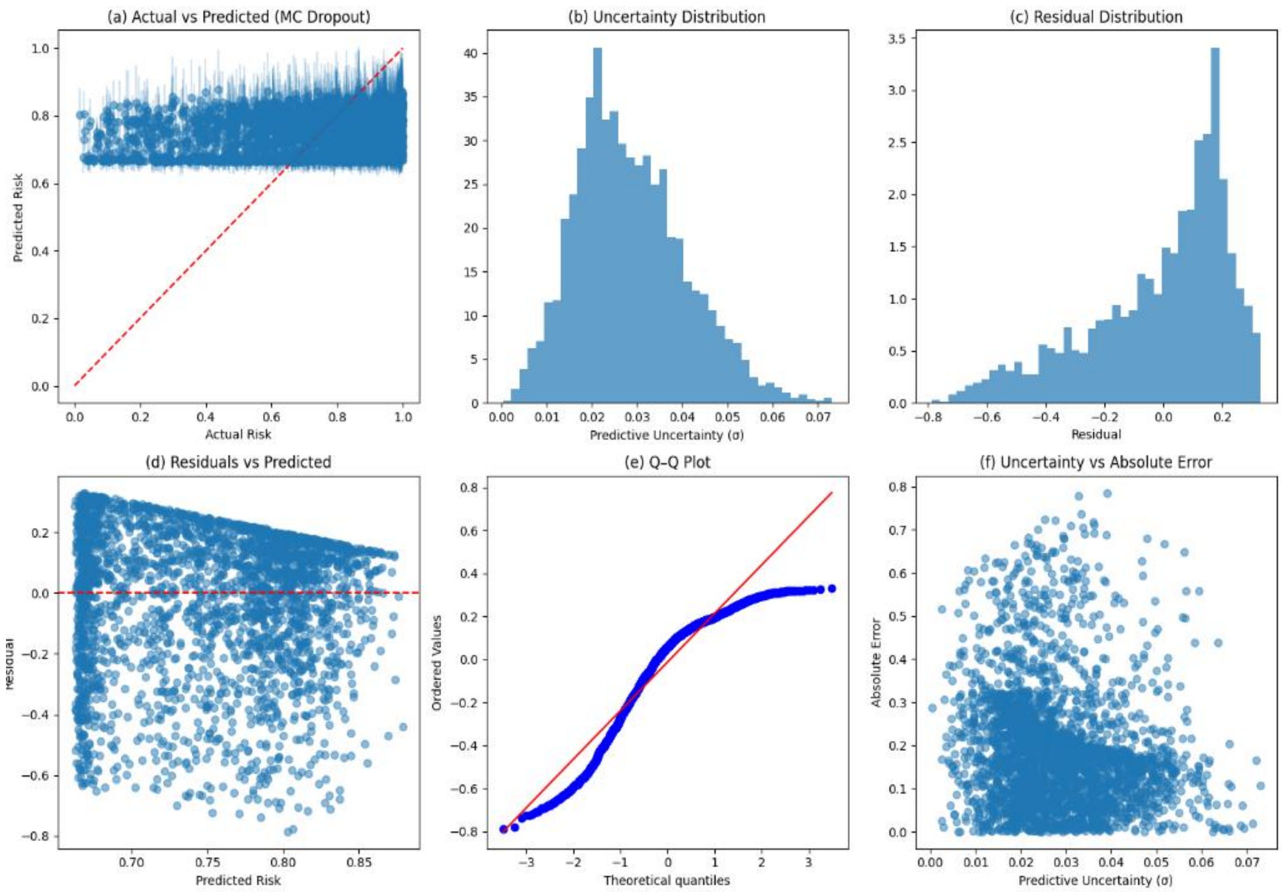

Figure 8: Diagnostic and Uncertainty Evaluation of the Monte Carlo (MC) Dropout Neural Network

Figure 8(a) displays the Actual vs Predicted plot of uncertainty bar, in which the dispersion around the diagonal indicates that predictive performance was moderate and stochastic variability. The uncertainty distribution (Fig. 8(b)) shows that there is concentrated yet significant predictive variance because of Monte Carlo sampling. Figure 8(c) indicates the residual distribution, which is asymmetric and widely distributed, indicating unequal prediction errors. Figure 8 (d) shows the residuals against the predicted values, pointing to the heteroscedastic behaviour and the pattern of systematic errors. The QQ plot indicated in Figure 8(e) proves non-normality. Figure 8(f) illustrates that there is a positive correlation between predictive uncertainty and absolute error.

These results show that MC Dropout is a more predictive variable, whereas the complete Bayesian strategy provides more quantitative uncertainty measurements in a more structured format. The results of ensemble integration follow.

4.4 Hybrid Model Integration and Ensemble Evaluation

In order to increase predictive robustness, the results of deterministic, stochastic, and Bayesian models were merged to Hybrid ensemble configuration. This integration will serve to stabilize prediction and be aware of uncertainty, and taps into complementary learning behaviors among architectures.

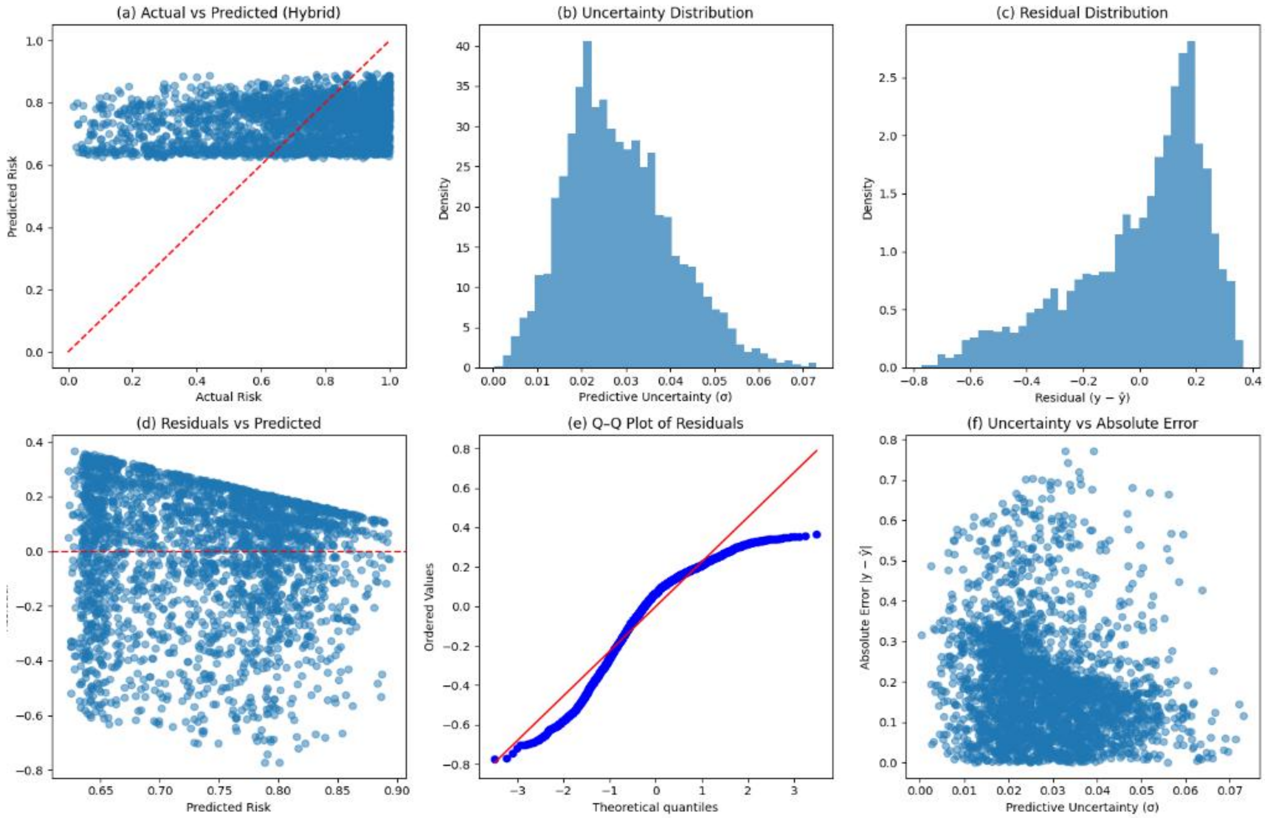

Figure 9: Comprehensive Diagnostic and Uncertainty Evaluation of the Hybrid Model

Figures 9 (a) shows the Actual vs Predicted plot in figure 9 (a) with moderate consistency with the ideal diagonal line, which means that there is a balance in predictive performance with some variation. The uncertainty distribution shown in Figure 9(b) is the calibrated predictive variance in terms of Monte Carlo sampling. The distribution of the residual, which is shown in Figure 9(c), is asymmetric and widely dispersed, indicating that the prediction errors are uneven. Figure 9(d) illustrates the residuals versus the predicted values, which reveals the heteroscedastic trends at various levels of risk. The QQ plot of Figure 9(e) indicates that residual behavior is not normal. Figure 9(f) shows that there is a positive association between predictive uncertainty and absolute error.

The ensemble is a little more stable on the regression performance, but still maintains the probabilistic properties that are passed on to the Bayesian component. The last subsection measures performance about displacement risk groups.

4.5 Class-wise and Overall Regression Performance

To sum up heterogeneity between the occupational displacement severities, prediction was defined into Low, Medium, and High-risk. The performance measures were calculated individually to assess stability over different levels of risk.

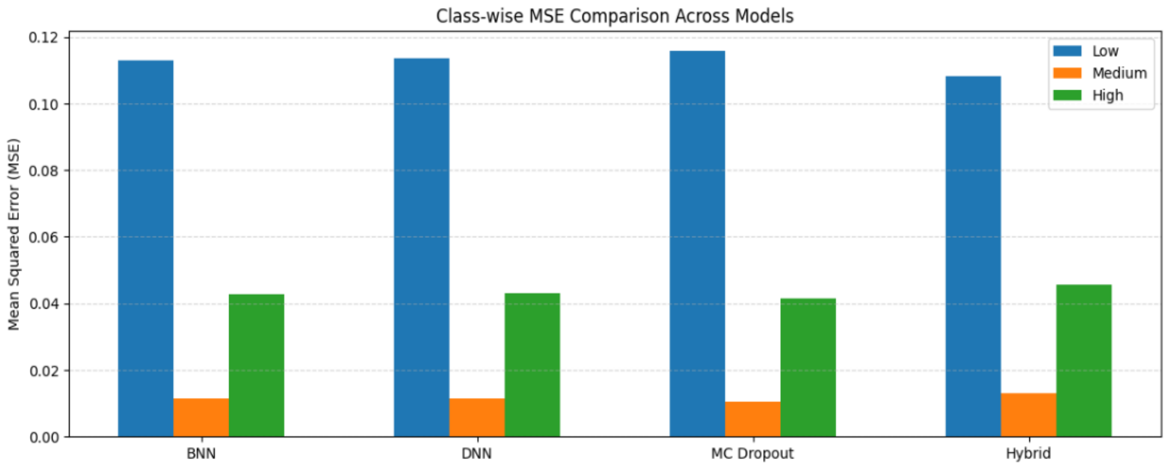

Figure 10: Class-wise Mean Squared Error (MSE) Comparison Across BNN, DNN, MC Dropout, and Hybrid Models

Figure 10 provides a comparison of the Mean Squared Error (MSE) of Low, Median and high risk of the displacement in four models on a class basis. The medium-risk class is the most consistent with the lowest MSE values in all the models, which means that it predicts better moderately vulnerable occupations. The Low-risk category is the most predictable with the greatest MSE, as it depicts more difficulty in predicting occupations that are stable. The best of the models is the Hybrid model, which has a slightly better performance in Low-risk, whereas MC Dropout has a slight benefit in High-risk. On the whole, the variances between models are comparatively low, implying similar predictive ability with minor gains realized by integrating the models.

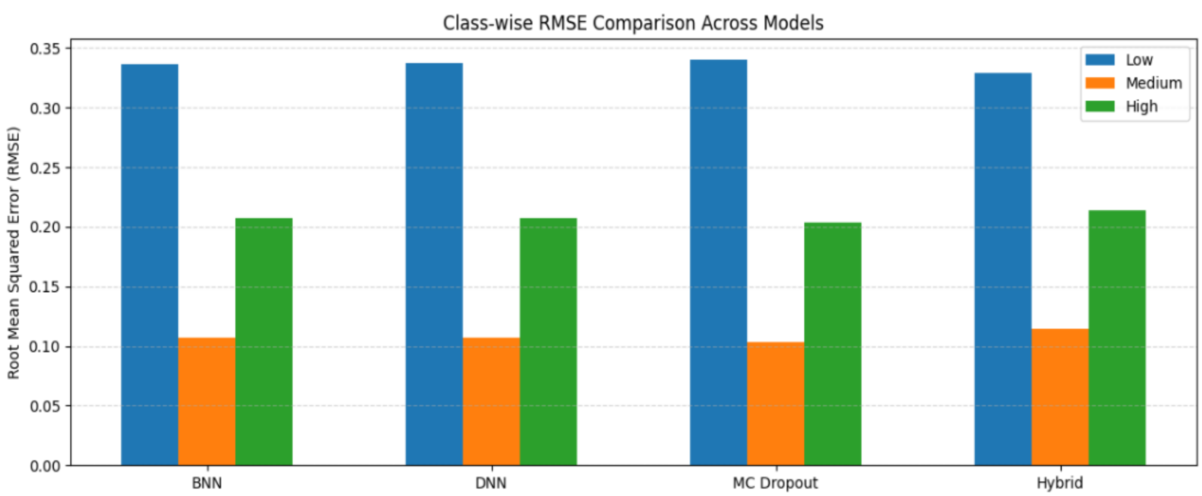

Figure 11: Class-wise Root Mean Squared Error (RMSE) Comparison Across BNN, DNN, MC Dropout, and Hybrid Models

Figure 11 shows the values of class-wise Root Mean Squared Error (RMSE) of Low, Medium, and High displacement risk in four models. The medium-risk category always has the lowest RMSE, and this implies that it has a higher prediction accuracy on moderately vulnerable jobs. The RMSE in the Low-risk class is the highest of all the models, indicating that there is more difficulty in accurately predicting the stable occupations. In the Low-risk category, the Hybrid model shows a little better performance, whereas in the high-risk category, it is MC Dropout that shows a little better performance. All in all, there is a minor difference in performance of models, suggesting that they have similar predictive performance with a minor advantage of integration among the ensembles.

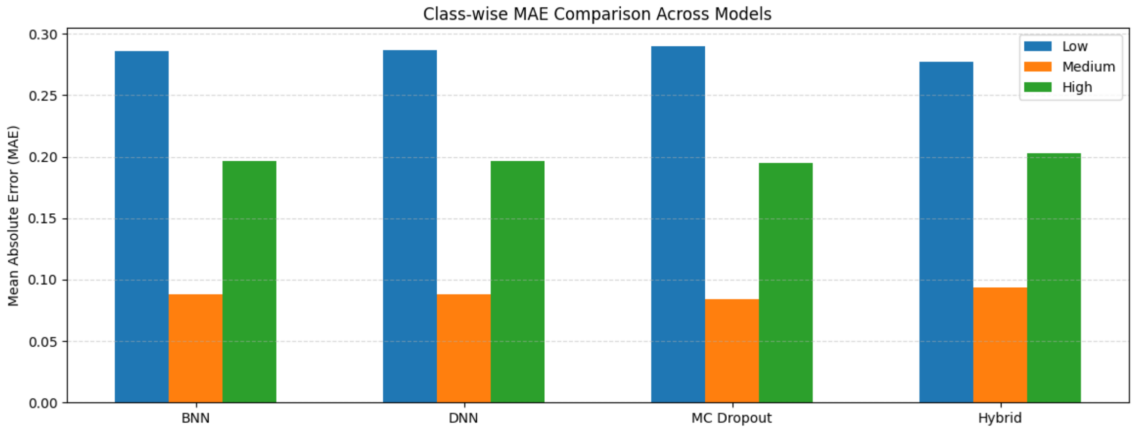

Figure 12: Class-wise Mean Absolute Error (MAE) Comparison Across BNN, DNN, MC Dropout, and Hybrid Models

In Figure 12, the values of Mean Absolute Error (MAE) are provided as the values of Low, Medium, and High displacement risk in the four predictive models. The Medium-risk category is always the one that has the lowest MAE and therefore, has a relatively better predictive accuracy of moderately vulnerable jobs. The category of Low-risk has the greatest MAE among models, and this implies that it is more difficult to estimate stable job profiles. The Hybrid model performs slightly better in the Low-risk category, whereas MC Dropout performs marginally competitively in the High-risk group. All in all, differences amongst models are slight, with similar predictive stability differences, with slight gains made by ensemble integration.

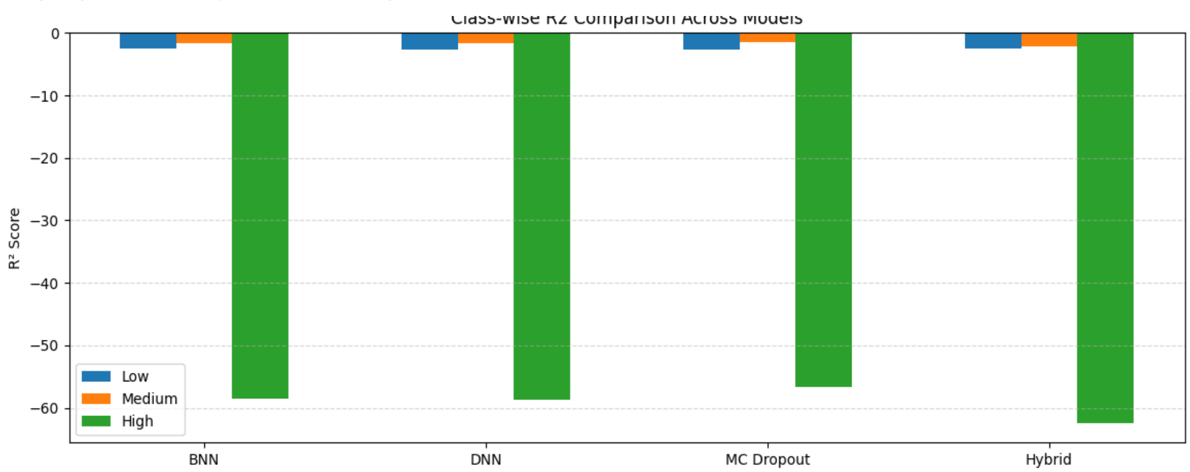

Figure 13: Class-wise R² Score Comparison Across BNN, DNN, MC Dropout, and Hybrid Models

Figure 13 shows the class-based R 2 score of the Low, Med, and High displacement risk models based on four models. The Medium-risk group has relatively more favorable (not so negative) values of R 2, and so, it has a comparatively better variance explanation. The Low-risk category shows moderately negative scores on the R 2 factor, which indicates a weak predictive fit. The High-risk category has significantly negative values of R 2 in all the models, indicating poor variance and a greater prediction problem with extreme-risk jobs. The model variations between models are some of the minor differences, with MC Dropout marginally bettering the performance of High-risk. All in all, the negative R 2 values indicate low variance conditions with a class-wise segmentation and less explanatory power.

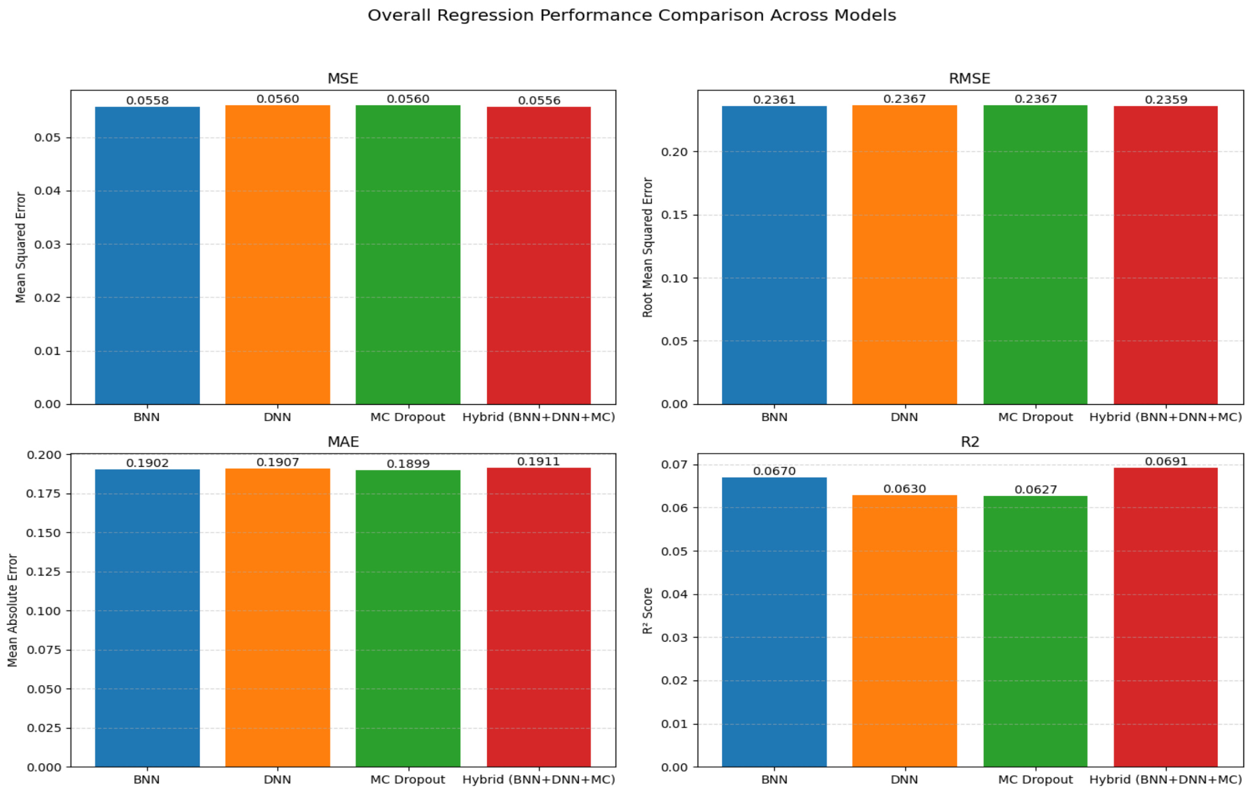

Figure 14: Overall Regression Performance Comparison of BNN, DNN, MC Dropout, and Hybrid Models

Figure 14 contrasts the overall regression performance by four models based on the measures of MSE, RMSE, MAE, and R 2. The hybrid model shows the lowest MSE and RMSE values, which means a little better predictive accuracy. MC Dropout outperforms the average performance of absolute error by a slight margin, with the lowest MAE. The Hybrid model also has the greatest R 2 value, implying a better variance explanation than the individual models. Variances across models are not very big, so the distinction in predictive skills is similar. In general, the findings demonstrate that ensemble integration has small performance advantages, and Bayesian-based methods have competitive accuracy coupled with the uncertainty estimation advantages.

In summary, the findings show that there is consistent convergence and architecture-independent competitive regression performance, as well as calibration of uncertainty meaningfully in probabilistic modeling. Although the use of ensemble integration produces gradual changes in the error measures, the key benefit of the offered framework is the possibility to give uncertainty-sensitive displacement of the workforce predictions in the context of AI-motivated transformation in the labor market.

4.6 Discussion

The empirical results show that the inclusion of uncertainty-aware probabilistic modeling results in a significant enhancement of the reliability and interpretability of AI-based prediction of workforce displacement. In model analyses, the Bayesian framework was shown to exhibit smoother validation behaviour, predictive intervals, and is much more stable in high-risk occupational sectors than deterministic architectures. This establishes the fact that uncertainty quantification is not a kind of auxiliary feature but a structural imperative when it comes to the model of dynamic vulnerability in the labor market. The assessments considered in the past concentrated on more or less static task-level or exposure-based assessments. As an example, Xu et al. (2025) [16] have created a BERT-based model to predict the automatability of tasks and presented the finding that routine tasks and semi-routine tasks have a higher risk of automation. Nevertheless, they produced deterministic results and failed to use predictive uncertainty and time flexibility. Conversely, the suggested Dynamic Uncertainty-Aware Bayesian Neural Model (DUA-BNM) generates probabilistic distributions of risks, which enables one to constantly reconsider the occupational risk as the AI exposure changes.

On the macro level, Occhipinti et al. (2024) [18] reviewed the disruptive effects of generative AI on the labor market, focusing on structural risk and without quantifying the likelihood of displacement. The findings of the current paper are not limited to the discussion of descriptive macro-risks but are relevant to the operationalization of quantitative, occupation-level, probabilistic forecasting. The Bayesian model proved to have calibrated dispersion in highly variable occupational categories and thus mapped macro-level disruption discourse into quantifiable predictive patterns. Recent literature has also focused on skill-based polarization. In low-skill-intensive economies, structural vulnerability patterns have been identified by Ganuthula and Balaraman (2025) [21] as exposed to greater automation. The same finding is congruent with the class-wise regression analysis in this study, where it was found that higher predictive variance and concentration of uncertainty were found to be in high-risk segments. As compared to descriptive polarization studies, though, the existing framework measures predictive dispersion and incorporates it directly into risk estimation. Likewise, Fenoaltea et al. (2024) [24] came up with an AI exposure index (AISE) to enhance the measurement accuracy of occupational AI exposure. Although the exposure indexing has the benefit of enhancing the validity of measurement, it lacks the ability to forecast dynamically. This paper incorporates exposure sensitivity within a probabilistic neural network to convert the image of a static exposure indicator into a future risk forecast, complete with a measure of uncertainty.

Deterministic neural networks performed competitively in terms of mean error over comparative assessments, but were unaware of variance, and tended to make overconfident forecasts in unstable labor markets. Better calibration was always done by the Bayesian architecture, especially on the heterogeneous occupational categories. The hybrid ensemble also made it more robust through the combination of deterministic stability and probabilistic interpretability. On the whole, the results prove the conclusion that the transition between deterministic exposure assessment and dynamic uncertainty-conscious forecasting is a significant methodological improvement. Predictive accuracy plus calibrated uncertainty. When integrating predictive accuracy with calibrated uncertainty, the proposed framework can be a policy-relevant, realistic tool in the context of the ever-accelerating AI automation, in terms of adaptive workforce planning.

5. CONCLUSION

This paper presented a Bayesian Neural architecture of Dynamic Uncertainty-Aware forecasting of workforce displacement during AI automation. The solution suggested combines probabilistic modelling, task heterogeneity, and temporal updating to produce risk predictions that are calibrated, not the exposure score of the task. The empirical findings show consistent convergence among the Bayesian, deterministic, and ensemble models, with the hybrid model slightly performing better. Notably, Bayesian-based architectures gave sensible quantification of uncertainty which promoted interpretability and policy relevance. The moderate explanatory power is the result of nonlinear and complex intrinsic dynamics of the labor markets and not methodological constraints.

To enrich the displacement modeling, future studies may include macroeconomic variables, wage elasticity variables, and demographic segmentation to capture a clear picture of displacement. Dynamic forecasting would be enhanced with longitudinal datasets of changing patterns of AI adoption. Also, it might be possible to integrate scenario-based simulation or reinforcement learning frameworks to facilitate proactive workforce policy planning in the context of alternative technological diffusion pathways.

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