Structural workplace factors contributing to Australia's persistent gender pay gap

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Abstract

Purpose – This study aims to investigate the organisational factors that contribute to Australia's persistent gender pay gap (GPG), which remains a challenge despite existing legislation. By analysing structural workplace factors like industry division and employer size, the authors use machine learning to build predictive models, moving beyond simply describing the problem to proactively identifying and addressing the specific drivers of pay disparity.

Design/methodology/approach – Using 2022–2023 data from the Workplace Gender Equality Agency (WGEA), the study analysed 7,800 Australian organisations. It used multiple machine learning models – including linear regression, random forest and neural networks – to predict the GPG based on employer and industry characteristics. Model performance was compared using R^2 and classification accuracy metrics.

Findings – Neural networks achieved the highest accuracy (91.9%), showing that employer size, sector and leadership composition are key predictors of the GPG. Sectors such as financial services, construction and mining exhibited the largest pay disparities. Surprisingly, the presence of flexible work policies correlated with higher GPGs, suggesting these policies may be reactive measures rather than indicators of equitable workplace culture.

Originality/value – This research is among the first to apply AI-driven algorithmic modelling techniques to the WGEA data set for GPG prediction. The paper offers a twofold contribution by providing novel insights into how specific organisational attributes influence pay equity: academically, it advances methodological lens within gender studies by applying machine learning to a field traditionally dominated by econometric or qualitative methods. Practically, it provides a powerful new tool for regulators and organisations to identify the specific drivers of the GPG, allowing them to target interventions precisely where they are most needed.

Keywords Gender pay gap, Workplace equality, Machine learning, Organisational predictors, Pay equity, Australian labour market

Paper type Research paper

1. Introduction

Despite decades of legislative efforts, corporate initiatives, and public awareness campaigns, the gender pay gap (GPG) remains an obstinate and pervasive issue across global labour

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markets. In countries such as the UK and Australia, gender pay transparency mandates have catalysed the availability of pay gap data at the organisational level. Yet, substantial differences persist: women continue to earn significantly less than men across sectors, roles and seniority levels (Rubery and Grimshaw, 2015; Si *et al.*, 2021). According to the latest Workplace Gender Equality Agency (WGEA) data, the average GPG for total remuneration stands at 21.8%, meaning women earn approximately 78 cents for every dollar earned by men (WGEA, 2023). This persistent disparity raises questions about the structural workplace factors that continue to influence pay inequities beyond individual choices or characteristics. While multiple studies have quantified the GPG at aggregate and occupational levels (Blau and Kahn, 2017; England, 2005), fewer have interrogated the specific organisational factors that exacerbate or mitigate these disparities. What is more, the application of predictive models to gender inequality, particularly those informed by feminist critiques of organisational practices, remains underdeveloped. This study, therefore, intends to make a dual contribution: empirically, by identifying the most salient predictors of organisational GPGs; and theoretically, by illuminating the structural and institutional mechanisms through which inequality is perpetuated.

The GPG has traditionally been explained through human capital theory (Becker, 1992), which attributes wage differences to variations in education, work experience or job tenure. However, feminist scholars have long contested the adequacy of these explanations, emphasising instead the role of systemic discrimination, occupational segregation and patriarchal organisational structures (Acker, 2006; Reskin and Bielby, 2005). Gender studies researchers underscore that gender pay disparities cannot be understood solely as outcomes of individual choices or meritocratic processes; rather, they are deeply embedded in institutional norms and labour market dynamics (Bridges and Nelson, 1989; Kelan, 2009).

At the organisational level, literature has identified several structural predictors of pay disparities. These include industry sector (Mandel and Semyonov, 2014), firm size (Bishu and Alkadry, 2017) and representation of women in leadership (Georgeac and Rattan, 2019). For instance, large employers with highly gendered leadership hierarchies often exhibit wider pay gaps, even when controlling for role type or job grade (Cohen and Huffman, 2007). Besides, the concentration of women in lower pay quartiles – a form of vertical occupational segregation – has been consistently linked to higher organisational-level disparities (Kacperczyk and Balachandran, 2018). However, these studies often treat predictors as isolated variables and rarely examine their interactive or compound effects.

Three major limitations persist in the current literature on organisational GPGs. First, while feminist scholarship has offered rich theoretical critiques of organisational inequality (Rodriguez *et al.*, 2023; Mavin and Yusupova, 2020), methodological advances have lagged. Much research remains qualitative, descriptive or explanatory, with limited integration of predictive analytics. This underdevelopment means structural predictors and interactions have been underexplored. Though it is known that factors such as leadership composition or flexible work options correlate with pay inequality (Bishu and Alkadry, 2017; Georgeac and Rattan, 2019), there is limited knowledge on which combination of variables best predicts large disparities and how these factors operate across contexts. Second, many studies rely on self-reported employee data or small-scale qualitative interviews, which – although rich in insight – do not generalise across organisations. Third, while economists and management scholars have increasingly used regression and causal inference techniques to study pay inequality (Kristjanpoller *et al.*, 2023), the application of machine learning (ML) methods remains relatively rare. Gender studies scholars have justifiably critiqued algorithmic approaches for their opacity and potential to replicate biases (D'Ignazio and Klein, 2023). Yet, when used transparently, unlike linear regression, which assumes additivity and linearity, ML methods can capture non-linear interactions and higher-order effects without prespecifying functional forms, revealing previously obscured patterns among predictors that may be missed in conventional models (Shu and Ye, 2023). This allows detection of subtle, compound patterns otherwise obscured. Therefore, there is an urgent need for interdisciplinary research that applies computational methods while remaining sensitive to feminist critiques of quantification and datafication (D'Ignazio and Klein, 2023).

To address these gaps, this study poses two interrelated research questions (RQs):

RQ1. What are the most important predictors of organisational gender pay gaps?

RQ2. And how well do combinations of structural and representational factors predict high or low pay disparities?

To answer these, we draw on WGEA's data set of 7,776 Australian employers from publicly available GPG reporting schemes. Using feature-rich employer-level data (including number of employees, industry division, quartile representation, flexible work policies and leadership composition), we build and evaluate multiple ML models (i.e. linear regression, random forest (RF), neural network) to predict the extent of GPGs and identify the key features driving these disparities.

The paper aims to contribute to gender studies in several ways. Firstly, it offers a methodological intervention by demonstrating how ML models can be used not merely for efficiency or automation but as tools for feminist inquiry – identifying where and how gendered inequalities are most entrenched. Secondly, it enhances theoretical understanding by showing that variables such as representation in upper quartiles and availability of flexible work policies interact in complex ways that shape gender pay outcomes. Third, the paper contributes to policy debates by identifying leverage points where organisational interventions are most likely to reduce pay gaps – thus informing compliance strategies for gender pay transparency regulations. From a broader epistemological standpoint, this study aligns with recent calls for "critical data feminism" (D'Ignazio and Klein, 2023), which encourages the use of quantitative tools to challenge power imbalances rather than reinforce them. By combining robust statistical methods with a gender-theoretical lens, we resist the reduction of inequality to simple metrics and instead foreground the organisational systems and social norms that sustain disparity.

2. Literature review

2.1 Research context

The GPG remains a persistent feature of labour markets globally, with organisational and structural factors playing a central role in shaping wage disparities between men and women (Blau and Kahn, 2017). While individual-level factors such as education and occupation partially explain these gaps, a growing body of literature emphasises the role of employer characteristics (Kunze and Miller, 2017; Ridgeway and Wu, 2021), industry context (Mandel and Semyonov, 2014; Galea *et al.*, 2015), organisational demographics (Cook and Glass, 2014; Papíková & Papík, 2024) and workplace policies (Lott and Klenner, 2018; Barns and Preston, 2022). The GPG represented a fundamental economic inequity in Australia's labour market, with significant implications for women's financial security, retirement outcomes and economic participation (Kennedy *et al.*, 2017). Despite decades of equal pay legislation, Australia continues to experience a substantial GPG, currently at 21.8% according to the latest WGEA data (WGEA, 2023). This persistent disparity impacts individual women's lifetime earnings and has broader economic consequences, with

PricewaterhouseCoopers (2022) estimating the total economic cost of the GPG in Australia at approximately $51.8bn annually.

2.1.1 Role of Workplace Gender Equality Agency data in research context. The WGEA provides Australia's most comprehensive gender equality data sets, collecting mandatory reporting from non-public sector employers with 100 or more employees. This data uniquely and comprehensively positions the WGEA as a critical resource for understanding workplace structural factors, offering unparalleled insights into organisational practices, industry-specific trends and longitudinal changes in gender pay equity.

2.1.2 Key structural workplace factors. 2.1.2.1 Occupational segregation. Occupational segregation (the concentration of women and men in different industries, occupations and roles) represents a fundamental structural factor in Australia's GPG. WGEA data (2022) documents persistent horizontal segregation across industries, with women comprising only 17.5% of employees in the mining sector compared to 78.3% in healthcare and social assistance. This segregation directly impacts pay outcomes, as Cassells *et al.* (2017) demonstrate that female-dominated industries pay on average 30% less than male-dominated industries for comparable skill levels.

2.1.2.2 Organisational hierarchies. The structure of organisational hierarchies significantly impacts gender pay equity through limited advancement opportunities for women. WGEA data demonstrates that women's representation decreases at each ascending level of management, with women holding 42.5% of management positions but only 22.3% of CEO roles (WGEA, 2023). This "pyramid" structure directly impacts the GPG by concentrating women in lower-paid positions.

Research by Fitzsimmons *et al.* (2021) identifies structural barriers in advancement pathways, including opaque promotion criteria, informal sponsorship networks and stereotyped leadership models. The "missing middle" phenomenon (where women drop out of the pipeline at mid-management levels) appears particularly pronounced in Australia compared to international benchmarks (McKinsey and Company, 2023). Acker's (2006) inequality regimes framework provides a lens for understanding these dynamics, conceptualising hierarchies as sites where gendered assumptions about leadership and merit are systematically reinforced. Human capital theory would suggest women's underrepresentation stems from experience or tenure gaps; however, discrimination frameworks and the inequality regimes perspective highlight how organisational norms and practices (rather than individual deficiencies) sustain gendered advancement barriers.

Organisational size also emerges as a significant variable, with Richard *et al.* (2013) demonstrating that larger organisations typically have wider GPGs at executive levels despite having more formalised equality policies. This suggests that organisational complexity and multiple hierarchical levels may inadvertently disadvantage women through increased opportunity for discretionary decision-making. Here too, the distinction between individual-level explanations and structural accounts is evident: while larger firms might claim greater policy sophistication, inequality regimes embedded in their hierarchies can neutralise formal equality initiatives.

2.1.2.3 Work arrangements. Flexible work arrangements (FWAs) and part-time employment accessibility significantly impact gender pay outcomes as can be seen in the last Australian Federal election and the reversal of a major Australian Liberal Party policy (2025). Pocock and Charlesworth (2017) document how the "flexibility stigma" disproportionately affects women's career progression and compensation, with flexible workers perceived as less committed. WGEA data confirms that while 68.3% of organisations have flexible work policies, only 5.2% have set targets for men's participation in flexible work (WGEA, 2022).

The “part-time penalty” emerges as a particular structural concern. Coelli (2022) quantifies this penalty at approximately 14% of hourly wages, even after controlling for human capital factors. This penalty compounds over careers, as part-time workers (predominantly women) receive fewer development opportunities and promotions, creating cumulative disadvantage.

2.1.2.4 Reward and promotion systems. Performance evaluation criteria and promotion pathways frequently contain structural biases that disadvantage women. Foley and Williamson (2019) document how seemingly neutral merit-based systems often privilege masculine behavioural norms and continuous, uninterrupted career patterns. WGEA data shows that only 44.7% of organisations analyse their promotions by gender, and only 17.9% set targets for gender composition of promotions (WGEA, 2022).

Pay negotiation processes emerge as a significant structural barrier. Barns and Preston (2022) demonstrate that individualised negotiation processes disadvantage women through gendered expectations and differential consequences for assertiveness. Organisations with transparent salary bands show significantly smaller GPGs (WGEA, 2023).

2.1.3 Industry structures. Industry-specific wage determination processes reveal significant structural variations. IBIS World industry reports (2023) document how male-dominated industries typically feature enterprise bargaining with strong union representation, while female-dominated industries rely more heavily on awards with limited bargaining power.

WGEA data (2023) reveals that the financial and insurance services sector maintains Australia’s largest GPG (27.5%) despite high overall wages, while public administration shows a significantly smaller gap (5.6%). This suggests industry-specific structural factors beyond occupational segregation.

2.1.4 Predictive modelling of gender pay gaps. Numerous studies have investigated the determinants of wage inequality using a range of analytical approaches. Kristjanpoller *et al.* (2023) used a causal inference model to estimate GPGs, analysing variables such as age, tenure, education level, occupation and industry. While traditional linear regression has long been the dominant method in this area (Blau and Kahn, 2017), more recent work increasingly applies ML methods to capture complex patterns and improve predictive accuracy. Bonaccolto-Töpfer and Schnabel (2022), for instance, utilised debiased ML and “stacking regression” ensemble methods [1] to estimate GPG more accurately than conventional approaches.

However, there is limited application of advanced ML techniques to Australian GPG data, particularly the comprehensive employer-reported large data sets such as these provided by WGEA. Our research addresses this gap by developing predictive models specifically focused on Australian workplaces, with particular attention to industry division and employer size as potential structural determinants of gender pay inequity.

2.2 Hypotheses

This section synthesises relevant literature to examine the structural predictors of organisational GPGs, leading up to the development of four hypotheses.

A longstanding body of research identifies both industry and organisational size as critical structural determinants of wage inequality, particularly gender-based pay disparities. Industry-specific cultural norms, regulatory frameworks and labour segmentation practices contribute to persistent gender wage gaps (England, 2005; Cha and Weeden, 2014). For example, male-dominated sectors such as construction, mining and financial services often exhibit steeper pay hierarchies and more rigid occupational segregation, exacerbating wage differentials (Tomaskovic-Devey *et al.*, 2006; Cohen and Huffman, 2007).

Additionally, the visibility and enforceability of equal pay legislation vary across industries. The financial services sector, despite being highly regulated, is frequently cited for high pay gaps due to bonus structures and executive compensation practices that disproportionately favour men (Rubery and Grimshaw, 2015). Mining and construction, characterised by long working hours and physically intensive tasks, often institutionalise masculine norms that restrict women's entry and advancement, further entrenching pay disparities (Watts, 2009; Galea *et al.*, 2015). These industry-level dynamics inform *H1*:

H1a. There is a statistically significant relationship between an employer's industry division (e.g. financial services, construction and mining) and whether an employer's GPG falls outside the WGEA's accepted target range of ±5%. [2]

Organisational size is widely discussed as a determinant of gender pay disparities, yet the literature presents a nuanced and sometimes contradictory picture. Larger firms often possess more formalised hierarchies, complex pay structures and embedded historical inequities, which may sustain or exacerbate gender pay disparities (Petersen and Saporta, 2004). While they may have more resources to implement diversity policies, the diffusion of accountability can dilute enforcement and oversight (Kalev *et al.*, 2006). Thus, on the one hand, large employers also tend to exhibit more occupational segregation and differentiated roles across levels and functions, which may widen pay gaps when gender is unevenly distributed across those roles (Reskin and Bielby, 2005). On the other hand, large organisations are more likely to implement standardised human resource practices, formal pay-setting mechanisms and structured diversity and inclusion initiatives, which may mitigate gender-based pay disparities (Richard *et al.*, 2013; Stamarski and Son Hing, 2015). Given these competing theoretical arguments and mixed empirical findings, the relationship between organisational size and compliance with gender pay equity benchmarks remains uncertain. Accordingly, we propose a non-directional hypothesis:

H1b. There is a statistically significant relationship between employer size and an employer's gender pay gap falling outside the WGEA's accepted target range of ±5%.

One of the strongest organisational correlates of a reduced GPG is the proportion of women in leadership and higher-paid roles. Increasing the representation of women in upper quartiles of pay is theorised to reduce wage inequality through several mechanisms: role-model effects, inclusive leadership cultures and reduced male-dominated gatekeeping in promotion and pay decisions (Eagly and Carli, 2007; Ely *et al.*, 2011). Empirical studies consistently show that gender-diverse executive teams are associated with lower organisational pay disparities (Miller and del Carmen Triana, 2009; Cook and Glass, 2014).

Moreover, higher female representation in leadership is linked to more equitable pay practices and greater organisational transparency (Kunze and Miller, 2017). Women's presence at senior levels also challenges the gendered nature of performance evaluations and discretionary pay, which are often biased in male-majority leadership contexts (Bishu and Alkadry, 2017). Therefore, we propose:

H2. A higher representation of women in upper pay quartiles within an organisation is reliably associated with a reduced gender pay gap.

While FWAs and carer leave policies are designed to improve work–life balance and bolster caregiving responsibilities, especially for women, a growing body of literature highlights the paradoxical effects of such policies on pay equality. These policies, when inadequately structured or stigmatised, can reinforce gendered labour divisions and penalise those who use them (Williams *et al.*, 2013; Abendroth and Den Dulk, 2011).

FWAs often lead to occupational downgrading, reduced visibility and limited access to leadership tracks, particularly when uptake is gender-skewed (Lott and Klenner, 2018). Similarly, secondary carer leave policies – commonly taken by men – are typically shorter and less comprehensive, implicitly reinforcing the expectation that women should be primary caregivers. Organisations that offer these policies but do not foster an egalitarian culture around their use may inadvertently deepen pay gaps by concentrating women in part-time or flexible roles with limited upward mobility (Cech and Blair-Loy, 2014).

Thus, while these provisions are associated with progressive organisational cultures, their presence without broader institutional support and gender-neutral uptake mechanisms may exacerbate disparities:

H3. The presence of flexible work arrangements and secondary carer leave provisions in an organisation is reliably associated with a higher gender pay gap.

The prediction of organisational GPG has traditionally relied on linear regression models and Oaxaca–Blinder decomposition techniques to isolate unexplained wage differences after accounting for observable characteristics (Blinder, 1973; Oaxaca, 1973). However, these models assume linearity, additivity and independence, which may not hold in real-world labour markets with complex and interacting variables.

Recent advances in ML provide new opportunities for uncovering hidden patterns in gender pay data. Neural networks and tree-based models (e.g. RFs, gradient boosting) can model nonlinear interactions between variables such as industry, firm size, workforce composition and policy variables without prespecified functional forms (Barredo Arrieta *et al.*, 2020). Such models also excel in classification tasks, offering predictive accuracy improvements over traditional linear models (Molnar, 2022).

Empirical studies comparing ML and traditional approaches find that ML models often outperform in predictive tasks, especially in HR analytics. For instance, Ridgeway and Wu (2021) used gradient boosting to classify firms with high pay gaps and found significant improvement over logistic regression models. This performance gain is particularly valuable in policy contexts where early identification of at-risk organisations is crucial. Thus, we posit:

H4. Advanced machine learning models (e.g. neural networks) are more effective than traditional linear models in predicting and classifying gender pay gaps based on structural workplace factors.

3. Methodology

3.1 Data and tools

This study used employer-reported data sets provided by the WGEA, with a specific focus on the 2022–2023 reporting period supplemented by historical data from prior reporting years where available.

The primary data source included variables related to GPG, workforce composition, industry classification and organisational size. Supplementary data sets were used to enrich the feature set with additional organisational characteristics and responses to workplace gender equality indicators. We drew on data from 7776 unique employers operating in Australia (see Table A1 and Table A2 for descriptive statistics of data in Appendix).

To address the long-standing issue that employers submit their reports at different points in the “annual cycle” (creating subjective timing effects), we reorganised the multi-year data set into three objective time-series intervals:

(1) Interval 1 (T1): Early-period reporting window;

(2) Interval 2 (T2): Mid-period reporting window; and

(3) Interval 3 (T3): Late-period reporting window.

These intervals were created by splitting the annual reporting cycle into equal-length segments aligned with WGEA’s submission timelines. All employer observations across years were mapped into these intervals based on their lodgement month.

The analytical pipeline involved four major phases: data preparation, linear statistical modelling, supervised ML using RFs and deep learning for both regression and classification tasks. For detailed information about the conduct of these phases, please refer to Supplementary materials.

3.1.1 Data preprocessing. Data preprocessing began with a rigorous data cleansing process in which all organisational records containing missing values, incomplete responses or entries labelled as “NC” (not calculable) for the 2022–2023 median total remuneration GPG were removed to prevent bias arising from unreliable reporting.

Categorical variables were incorporated into regression models using standard dummy coding, with industry divisions operationalised through ANZSIC-based classifications and one category omitted as the reference group to support meaningful coefficient interpretation.

Organisational characteristics were treated similarly to reduce multicollinearity, ensuring coefficients reflected marginal differences in average GPG relative to the baseline category, although tree-based and neural network models learn relationships directly without requiring reference groups.

Employer size was coded using WGEA’s five organisational scale categories and label encoded from 0 to 4 to preserve ordinal structure, while flexible work and secondary carer leave arrangements were coded as binary organisational indicators. All percentage and monetary variables were converted into numeric formats prior to analysis to maintain computational consistency.

Employers were also assigned to one of three time-series intervals (T1–T3) based on submission timestamps, allowing consistent temporal comparisons across organisations with differing payroll cycles. Workplace policy variables derived from WGEA questionnaire responses captured the structural presence of policies rather than their uptake or effectiveness, aligning with the study’s organisational-level analytical focus.

3.1.2 Variable screening and ordinary least squares development. Initial variable screening involved computing Pearson correlation coefficients to identify predictors with meaningful linear associations with the average total remuneration GPG. Variables exhibiting weak relationships or substantial multicollinearity were excluded, including base salary GPG measures that duplicated variance captured by total remuneration indicators.

A multiple linear regression model was then estimated using the OLS function from the statsmodels package in Python. Variables with absolute correlation coefficients above 0.18 were initially considered, and the final specification retained only predictors with statistically significant effects ($p < 0.05$). Across all models, the dependent variable was the employer-level average total remuneration GPG (%). Explanatory variables included industry division indicators, organisational size, gender composition across pay quartiles, female representation in senior leadership, overall workforce gender composition, binary indicators for flexible work and secondary carer leave policies and time-interval controls (T1–T3) capturing reporting-cycle timing.

3.1.3 Random forest regression. To increase predictive capacity and assess non-linear relationships, an RF regression model was implemented using the RF regressor [3] from the "scikit-learn" library. This model provided a robust benchmark by capturing complex interaction effects between features. Model performance was assessed through predicted-versus-actual comparisons and standard metrics, including mean squared error (MSE) and R-squared (R^2) values. Feature importance scores generated from the model were also used to rank predictors based on their contribution to gender pay disparities.

3.1.4 Deep learning approaches. Two deep learning models were designed and trained using the Keras API. [4] The first was a regression model that predicted continuous GPG values, while the second classified employers as having above or below average GPGs, using the national average GPG of 21.8% as the threshold.

Both models used an architecture consisting of an input layer followed by two hidden layers with 64 and 32 ReLU-activated nodes, [5] respectively. For the regression task, the output layer comprised a single linear neuron optimised with MSE loss. [6] For the classification task, the output layer used a sigmoid activation function [7] and was trained using binary cross-entropy loss. [8] The Adam optimiser [9] was used in both models.

The regression neural network achieved an MSE of 0.0049 and a*n* R^2 score of 0.745, indicating strong predictive validity. The classification network achieved 91.9% accuracy, effectively distinguishing employers with above-average GPGs. A confusion matrix revealed balanced sensitivity and specificity, though there was a slightly higher tendency to misclassify below-average GPG instances as above average (a false negative result).

3.1.5 Model benchmarking. Predictive performance was benchmarked across linear regression, logistic regression, decision tree and neural network models using a consistent data-handling and evaluation pipeline. This ensured fair and reproducible comparisons across modelling approaches.

The data set was split into training, validation and test sets using a stratified 70–15–15 partition based on GPG intervals, preserving the distribution of low-, medium- and high-GPG organisations and reducing sampling bias. Within the training set, five-fold cross-validation was applied. Neural network models additionally used early stopping based on validation loss to mitigate overfitting.

The final model evaluation was conducted on a held-out test set. Performance was assessed using accuracy, precision, recall and F1-score for classification tasks, and RMSE and MAE for continuous outputs, enabling comparison of predictive accuracy and model robustness across methods.

3.2 Descriptive overview and initial exploration

Following data cleaning and transformation, the data set comprised observations from the 2022–2023 WGEA employer reports, merged with encoded responses to organisational practices, policies and demographic composition. Initial exploration through correlation analysis identified several variables with moderate to strong linear associations ($|r| > 0.18$) with the dependent variable: average total remuneration GPG (%).

Our analysis primarily focuses on the 2022–2023 reporting year, which is the first year of mandatory employer-level GPG disclosure in Australia. While historical submissions were used to construct reporting intervals (T1–T3) to address reporting-cycle timing effects, mean GPG values were calculated within the 2022–2023 reporting framework rather than pooled across years.

Highly collinear features were excluded to avoid multicollinearity in the regression model. Specifically, features such as "Median total remuneration GPG (%)", "Average base salary GPG (%)" and "2022–23 Median base salary GPG (%)" were removed from model input variables, a decision guided by both domain relevance and empirical correlation structure.

3.3 Linear regression

As shown in Table 1, statistically significant predictors included the percentage of women in the upper quartile (negative coefficient), percentage in the upper-middle quartile (positive coefficient) and categorical indicators for industry divisions such as “Health Care and Social Assistance” and “Other Social Assistance Services”. These coefficients suggest that greater female representation in higher pay bands is associated with a reduced pay gap, aligning with prior literature on structural inequality in remuneration (WGEA, 2024).

The model achieved an adjusted R^2 of approximately 0.31, indicating that while some of the variation in GPG is explained by the selected predictors, non-linear or latent interactions may require more flexible modelling techniques.

3.4 Random forest regression

To relax the linearity and additivity assumptions of OLS, we estimated a RF regression using the same predictors. RF models capture non-linear relationships and interactions among remuneration, workforce composition and organisational characteristics without prior specification. The model achieved strong performance ($MSE = 0.0053$; $R^2 = 0.72$), representing a modest improvement over the linear model (Table 2).

The main contribution of the RF approach lies in its feature importance analysis. The most influential predictors were upper-quartile remuneration, the percentage of women in the lower and upper pay quartiles and lower-quartile remuneration measures (Table 2). This pattern suggests that pay dynamics at the top of the distribution play a disproportionate role in shaping the overall GPG, while gender composition exerts differential effects across pay quartiles rather than a uniform influence.

Importantly, the RF model reveals non-linear and interaction effects absent from linear specifications. The impact of women’s representation in the upper quartile is non-monotonic, with larger effects emerging beyond certain thresholds, while the influence of lower-quartile gender composition depends on upper-quartile pay levels, indicating cross-quartile interactions. Additional non-linearities were observed for overall workforce gender composition, employer size and industry, implying that similar levels of representation or remuneration can have different effects across organisational and sectoral contexts.

3.5 Neural network regression

To further capture non-linear relationships, a deep neural network (DNN) regression model was implemented using the Keras API (TensorFlow backend). The hidden layers enabled the network to learn complex patterns in the data through non-linear activation functions. The final layer produced a [10] single numeric output representing the model’s predicted probability that an observation belonged to the positive class.

The neural network achieved strong predictive performance with an MSE of 0.0049 and R^2 score of 0.7452, indicating that nearly three-quarters of the variance in GPG could be explained by the model’s feature set. This significantly outperformed both the linear and RF models.

The results underscore the utility of neural architectures in modelling complex pay disparities that likely stem from a combination of policy implementation, industry norms and demographic structuring.

Table 1. OLS regression output: coefficients, standard errors and p-values

Dep. variable	Average total remuneration GPG (%)	*R*-squared	0.391
Model	OLS	Adj. R-squared	0.39
Method	Least squares	F-statistic	554.8
Date	Sat, 19 April 2025	Prob (F-stat)	0
Time	113,248	Log-Likelihood	5,943.3
No. observations	7,791	AIC	−1.19E + 04
Df residuals	7,781	BIC	−1.18E + 04
Df model	9		
Covariance type	Nonrobust		

	Coeff	Std err	t	$p>\|t\|$	[0.025	0.975]
Constant	0.0862	0.005	15.728	0	0.075	0.097
Upper quartile % women	−0.5689	0.013	−44.1	0	−0.594	−0.544
Upper-middle quartile % women	0.4242	0.012	35.581	0	0.401	0.448
Total workforce – average total remuneration ($)	−3.24E-06	2.91E-06	−1.112	0.266	−8.95E-06	2.47E-06
Upper quartile – average total remuneration ($)	1.22E-06	7.24E-07	1.681	0.093	−2.02E-07	2.64E-06
Upper-middle quartile – average total remuneration ($)	9.76E-07	7.35E-07	1.327	0.184	−4.48E-07	2.40E-06
Lower-middle quartile – average total remuneration ($)	1.07E-06	7.70E-07	1.384	0.166	−4.44E-07	2.57E-06
Lower quartile – average total remuneration ($)	9.88E-07	7.51E-07	1.316	0.188	−1.37E-06	1.57E-06
Class_other social assistance services	−0.0644	0.007	−9.209	0	−0.078	−0.051
Division_health care and social assistance	0.0389	0.005	7.632	0	0.029	0.049

Omnibus	1,159.889	Durbin–Watson	1.952
Prob (omnibus)	0	Jarque–Bera (JB)	12161.356
Skew	−0.368	Prob (JB)	0
Kurtosis	9.076	Cond. no.	4.22E + 06

Note(s): Standard errors assume that the covariance matrix of the errors is correctly specified. Total workforce – average total remuneration represents the mean total pay across all employees, providing an overall benchmark for earnings. The upper, upper-middle, lower-middle and lower quartile average total remuneration figures report the mean remuneration within each quartile of the workforce, ranked from highest to lowest earners. Together, the quartile measures illustrate how remuneration is distributed across the workforce and highlight differences between higher- and lower-paid employee group
Source(s): Authors' own work

Table 2. Performance and feature importance list of random forest model

Metric	Score
Model performance	
Mean squared error (MSE)	0.0053
R^2 score	0.7272
Top 10 most important features	
Feature	Importance
Upper quartile – average total remuneration ($)	0.267394
Lower quartile % women	0.233624
Upper quartile % women	0.229031
Lower quartile – average total remuneration ($)	0.056409
Lower–middle quartile % women	0.038275
Lower–middle quartile – average total remuneration ($)	0.037101
Total workforce % women	0.018024
Upper–middle quartile % women	0.017547
Upper–middle quartile – average total remuneration ($)	0.016324
Employer name_encoded	0.013145

Source(s): Authors' own work

3.6 Neural network classification model

The neural network regression output was converted to a binary classification using a 0.5 probability threshold, predicting whether an employer's GPG was above or below the 2024 national average of 21.8% (WGEA, 2024). Default hyperparameters were used to establish a transparent baseline model. A two-layer DNN with a sigmoid output was used.

As shown in Table 3, the classifier achieved 91.9% accuracy on the test set, with balanced sensitivity and specificity. While false positives ($n = 70$) indicate a slight tendency to overpredict above-average GPG, overall performance suggests strong practical utility for identifying high-risk employers.

Benchmark comparisons show lower accuracy for logistic regression (86.14%) and decision tree models (83.71%), confirming the superior predictive performance of the neural network. Even modest accuracy gains correspond to large differences in misclassified employers, underscoring the model's relevance for regulatory and policy applications.

3.7 Summary of predictive insights

Across time intervals (T1–T3) and modelling approaches, several organisational characteristics consistently emerged as key predictors of GPGs. These included gender

Table 3. Neural network model results

Regression results		Classification results	
Metric	Value	Metric	Value
MSE	0.085	Accuracy	0.919
R-squared	0.745		
Confusion matrix: GPG classification			
	Predicted 0	Predicted 1	
Actual 0	1120	70	
Actual 1	56	313	

Source(s): Authors' own work

composition in the upper and lower pay quartiles, employer size, industry sector and the presence of flexible work and secondary carer leave policies. The consistency of these predictors across linear, ensemble and neural network models strengthens confidence in their substantive importance and highlights the structural nature of GPG disparities.

While all models were informative, neural networks demonstrated superior capacity to capture complex, non-linear relationships among organisational characteristics and pay outcomes. Their performance indicates that gender pay inequality reflects interacting structural factors that extend beyond simple linear effects, underscoring the value of ML for identifying deeper patterns and informing policy responses.

4. Discussion

4.1 Interpretation of results

Results from both linear regression and ML models support the alternative hypothesis that structural workplace characteristics significantly shape GPG outcomes among Australian employers. The superior predictive performance of neural network models indicates that these relationships are complex and non-linear.

Linear regression results show that higher female representation in senior pay quartiles is associated with lower GPGs, consistent with prior research on vertical segregation and the undervaluation of female-dominated roles (Charlesworth and Smith, 2018; WGEA, 2023). This finding reinforces the importance of leadership representation in addressing pay inequity. Industry division also emerged as a strong predictor, with construction, mining and financial services exhibiting persistently higher GPGs, aligning with evidence of sector-specific wage structures in male-dominated industries (IBISWorld, 2023; Fitzsimmons *et al.*, 2021).

Regression results further indicate higher reported GPGs among organisations offering flexible work (+3.15%) and secondary carer leave (+1.5%). While counterintuitive, this pattern supports arguments that such policies are often introduced reactively following the identification of inequities rather than as proactive interventions (Cooper and Baird, 2022). Where flexible work is stigmatised or associated with reduced commitment, it may reinforce occupational segregation and widen pay gaps (Kelliher and Anderson, 2010). Conversely, when genuinely supported, flexible arrangements can reduce pay disparities by sustaining labour market attachment (Chung and Van der Horst, 2018; Goldin, 2014), indicating that policy impact depends on organisational norms.

The neural network regression achieved an R^2 of 0.7452, explaining nearly 75% of the variation in GPG outcomes, while the classification model achieved 91.9% accuracy in predicting above-average GPGs. Together, these results demonstrate that non-linear structural factors (particularly employer size, industry division and pay-quartile composition) are reliable and substantively important predictors of gender pay disparities in the Australian context.

4.2 Theoretical contributions

This study advances theoretical understanding of the GPG by situating structural workplace factors within established frameworks of inequality. Building on Acker's (2006) concept of inequality regimes, the findings illustrate how organisational hierarchies, industry segmentation and flexibility policies embed cultural and structural practices that sustain inequities even when formal equality measures exist. Demonstrating that systemic organisational dynamics more strongly predict disparities, our results also highlight the limitations of human capital explanations, which attribute wage differentials to education or experience. In doing so, the study contributes to feminist critiques of labour markets by showing how predictive modelling can shed light on the structural mechanisms through which inequality persists.

4.3 Methodological contributions

The results of this study are well aligned with the findings from the literature review, particularly regarding the impact of organisational structures, pay distribution and industry segmentation on GPGs. However, the key contribution of this study is the practical application those theoretical insights through ML models built on real-world Australian data.

This represents one of the first instances of applying advanced ML models (specifically RFs and neural networks) to the large-scale WGEA data set. As such, the study not only fills a methodological gap in existing literature but also provides a practical foundation for data-informed gender equity policy interventions in Australia. Whereas most prior research has relied on regression-based explanatory models, this study demonstrates the value of predictive analytics in identifying complex, non-linear relationships among employer size, industry division, workforce composition and policy variables. The combination of ML and publicly available workplace data offers a scalable and objective approach to identifying where the greatest equity risks lie, and how these might be addressed moving forward.

4.4 Implications for policy and organisations

This study has important implications for policymakers and organisations. The strong performance of the binary classification model highlights the potential of predictive analytics for targeted regulatory monitoring. For agencies such as the WGEA, ML tools could support risk-based audits by identifying high-risk employers, improving enforcement efficiency and reducing resource strain. This application aligns with growing interest in explainable AI for analysing complex social outcomes (Barredo Arrieta *et al.*, 2020; Molnar, 2022).

Organisations can similarly apply predictive modelling internally to identify emerging pay inequities and enhance transparency in remuneration processes. Such proactive use of workforce analytics supports early intervention and fairer pay structures, consistent with broader evidence on GPGs (Blau and Kahn, 2017).

The findings also emphasise leadership representation as a critical lever for change. Consistent with Goldin *et al.* (2017), persistent gender pay disparities largely arise from structural barriers in career progression rather than workforce entry. Organisations should therefore prioritise leadership development, mentoring and gender-equitable succession planning. Regulators may further support progress through governance targets, disclosure requirements or incentives aimed at executive-level gender balance.

Crucially, the association between higher GPGs and flexibility-related policies underscores that policy adoption alone is insufficient without cultural change. Embedded organisational norms can perpetuate inequality despite formal provisions. The part-time penalty (estimated at 14% of hourly wages (Coelli, 2022)) and persistent flexibility stigma further illustrate how cultural dynamics can undermine work–life initiatives.

The consistently higher GPG in the construction, mining and financial services sectors highlight the necessity for industry-specific interventions that move beyond uniform solutions. In mining and construction, disparities are often driven by masculine norms and physically intensive task structures that restrict women's career advancement. Conversely, the financial sector's high GPG (recorded at 27.5%) is frequently attributed to bonus structures and executive compensation practices that disproportionately favour men. These sectoral variations demonstrate that industry-specific structural factors, such as wage determination processes and the presence of "inequality regimes", create distinct environments where gendered inequities are perpetuated. Tools such as the GPG Assessment

Heat Map (Supplementary materials) can assist organisations in benchmarking their position within sectors and identifying targeted responses.

When considering these sectoral aspects, other significant organisational factors such as employer size and leadership composition must be integrated, as they lead to different GPG indicators. Large employers often exhibit wider gaps due to complex hierarchies that provide more opportunities for discretionary, and potentially biased, decision-making. Furthermore, indicators regarding workplace policies can be paradoxical; for instance, the presence of FWAs is often correlated with higher GPGs, suggesting these policies may be reactive measures rather than signs of an equitable culture.

4.5 Limitations

Despite strong predictive performance, several limitations should be considered. Firstly, the WGEA data set excludes small businesses and public sector organisations with fewer than 100 employees, limiting generalisability across the Australian economy. It also omits gig, contract and unpaid labour, which disproportionately include feminised occupations such as clerical and caregiving work. This exclusion may bias national GPG estimates and overlook relevant improvement pathways.

Secondly, the data capture only the presence of workplace policies, not their scope, uptake or intensity. As a result, observed associations between flexibility-related policies and higher GPGs should be interpreted as reflecting underlying structural or cultural dynamics rather than policy effectiveness.

Lastly, the absence of individual-level variables (including tenure, education, ethnicity, disability and job role) limits the ability to fully capture the complexity of gender pay disparities and may oversimplify their underlying determinants.

4.6 Future research directions

Future research should extend this study through longitudinal analyses to examine how structural predictors of the GPG evolve over time and to assess the effectiveness of policy and organisational interventions. Such approaches would clarify whether observed changes reflect meaningful progress or shifting structural dynamics.

Intersectional modelling represents another important direction. Incorporating factors such as age, ethnicity and disability would provide a more nuanced understanding of gender pay disparities and recognise that inequality operates differently across intersecting identities.

Lastly, future work should prioritise the inclusion of small businesses, the gig economy and unpaid labour by developing tailored metrics for non-standard employment. Addressing these gaps is essential for capturing the full scope of gender pay inequality and informing inclusive policy responses.

5. Conclusion

This study applies advanced ML techniques to gender pay research, demonstrating how predictive approaches can uncover complex, non-linear patterns that traditional models often overlook. Secondly, it identifies key structural predictors such as industry context, employer size and leadership representation that shape pay outcomes and reinforce theoretical perspectives on systemic inequality. Thirdly, it provides practical insights for policymakers and organisations by exhibiting how predictive analytics can guide targeted, evidence-based interventions to combat gender-based pay disparities.

Notes

[1.] Debiased ML reduces bias in parameter estimation when confounders exist, while stacking regression is an ensemble approach combining multiple models to improve predictive accuracy.

[2.] WGEA defines an “acceptable” organisational GPG as being within ±5%. A GPG greater than +5% indicates that men are paid more, on average, than women (i.e. the gap favours men). Whereas a GPG less than -5% indicates that women are paid more, on average, than men (i.e. the gap favours women). Values between -5% and +5% fall within WGEA’s acceptable tolerance and are not considered materially imbalanced. Thus, “falling outside the WGEA’s accepted range of ±5%” specifically means the organisation exhibits a substantial gender pay imbalance in either direction.

[3.] This is an ensemble ML method that predicts outcomes by combining the results of many decision trees, improving accuracy and reducing the risk of overfitting compared to a single tree.

[4.] Deep learning models were built and trained using Keras API, a high-level application programming interface (API) that streamlines the process of designing and training neural networks by providing user-friendly access to TensorFlow’s computational backend.

[5.] Each using a ReLU activation function that allows the model to capture non-linear relationships by outputting positive values while setting negative ones to zero.

[6.] The model’s output layer contained a single linear neuron, which produced continuous numerical predictions and was trained to minimise error using MSE as the loss function.

[7.] Generates probabilities between 0 and 1.

[8.] Measures the difference between predicted probabilities and actual class labels.

[9.] Adaptively adjusts learning rates for each model parameter to efficiently minimise loss during training.

[10.] The default threshold of 0.5 was applied to the neural network output, with values above 0.5 assigned to one class and values at or below 0.5 assigned to the other.

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Further reading

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Appendix. Descriptive statistics

Table A1. Categorical variables summary

Variable	Unique values	Most frequent (top)	Frequency of top
Employer name	7,776	Lutheran church of Australia Queensland District	18
Industry (ANZSIC division)	19	Health care and social assistance	1122
Industry (ANZSIC class)	436	Other social assistance services	422
Employer size range	5	< 250 employees	4002

Table A2. Numerical variables summary (key metrics)

Variable	Mean	SD	Min.	Median	Max.
Gender pay gap (GPG) metrics					
Average total remuneration GPG (%)	0.130	0.144	−0.907	0.120	0.786
Average base salary GPG (%)	0.106	0.136	−1.078	0.097	0.786
Median total remuneration GPG (%)	0.104	0.190	−6.234	0.086	0.880
Median base salary GPG (%)	0.081	0.185	−6.489	0.061	0.880
2022–2023 median total remuneration GPG (%)	0.090	0.212	−4.448	0.079	0.731
2022–2023 Median base salary GPG (%)	0.070	0.213	−5.022	0.061	1.000
Workforce composition (% women)					
Total workforce % women	0.468	0.247	0.000	0.470	1.000
Upper quartile % women	0.387	0.266	0.000	0.360	1.000
Upper-middle quartile % women	0.450	0.277	0.000	0.450	1.000
Lower-middle quartile % women	0.494	0.264	0.000	0.510	1.000
Lower quartile % women	0.540	0.240	0.000	0.560	1.000
Remuneration metrics ($)					
Total workforce avg total remuneration	$121,566	$52,370	$9,000	$111,000	$778,000
Upper quartile avg total remuneration	$193,180	$113,919	$30,000	$168,000	$2,419,000
Upper-middle quartile avg total remuneration	$121,603	$51,486	$6,000	$111,000	$605,000
Lower-middle quartile avg total remuneration	$97,489	$36,925	$1,000	$89,000	$483,000
Lower quartile avg total remuneration	$74,895	$24,165	$0	$70,000	$389,000

Supplementary material

The supplementary material for this article can be found online.

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