Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

AI-Powered Decision Making in HRM: Designing Dynamic Tariff Plans for Workforce Compensation

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Abstract:
The adoption of Artificial Intelligence (AI) in the Human Resource Management (HRM) is fundamentally changing the way things were done, and the compensation and benefits are one of the most affected spheres. The paper discusses the paradigm shift of a one-size-fits-all model of compensation to a dynamic AI-based tariff plan. The old models, which are usually grounded on historical standards and annual evaluations are no longer suitable to the new workforce, which is dynamic, flexible, and worldly. They do not consider the market variations in real-time, the nuances of performance of each individual, the values of the skills of the employees and their own preferences. The article assumes that AI-inspired systems, which can be based on machine learning, natural language processing, and predictive analytics, have the potential to create and operate dynamic tariff plans that are fair, competitive, and extremely personalized. We explore the architectural aspects of such systems such as the data aggregation, predictive modelling to market rates and flight risk, ontology mapping of skills, and the optimization of personalized benefits. The methodology is based on the conceptual analysis of AI applications with the support of case vignettes and the overview of the current technological platforms. It is demonstrated in the analysis that AI can help advance pay equity by reducing human bias, improving retention with predictive analytics, and streamlining compensation budgets. Nonetheless, the major issues are mentioned, such as bias in algorithms, the question of data privacy, the black box problem of AI decision-making, and the possibility of dehumanization of HR practices. The conclusion states that to be successful in the talent war, the use of AI in compensation planning is not just a choice but a strategic necessity to organizations. The key is a symbiotic strategy that involves AI managing the data-intensive computing and pattern recognition, whereas HR specialists can ensure strategic management, governance, and understanding of their staff.

Keywords: Artificial Intelligence, Human Resource Management, Dynamic Compensation, Tariff Plans, Pay Equity, Predictive Analytics, Machine Learning, Algorithmic Bias, Talent Retention, Strategic HRM.

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Introduction:

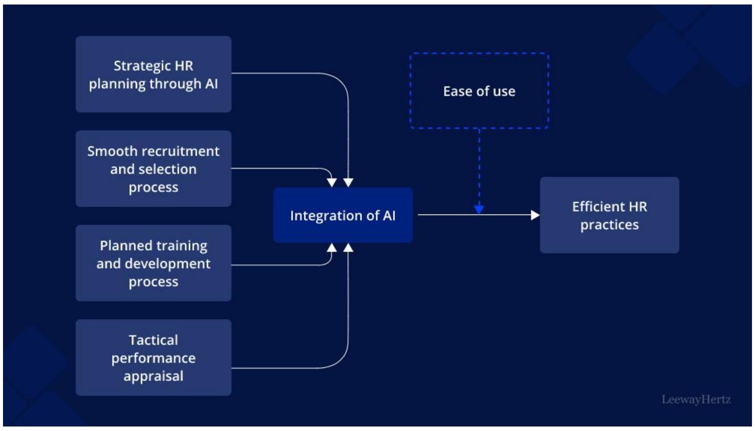

Fig 1. AI in HR
(Source: Leewayhertz, 2025)

Traditionally, Human Resource Management (HRM) has been viewed as an administrative and support service that tends to be technologically slow in implementing changes compared to other business departments (Oda, 2023). Its fundamental operations such as recruitment, performance management and compensation have been typified by manual intervention, standardized courses of action as well as cyclic continuous review periods. Compensation management, especially, has been pegged on fixed tariff plans namely, structured scales of pay, grades, and bands based on job titles, seniority and annual market surveys. Although these models offer a pretense of organization and certain predictability, they are essentially inflexible. They find it difficult to fit an environment of change in the modern day business world that is characterized by fast technological evolution, the emergence of the gig economy, global talent pools, and an escalated competition over specialized skills.

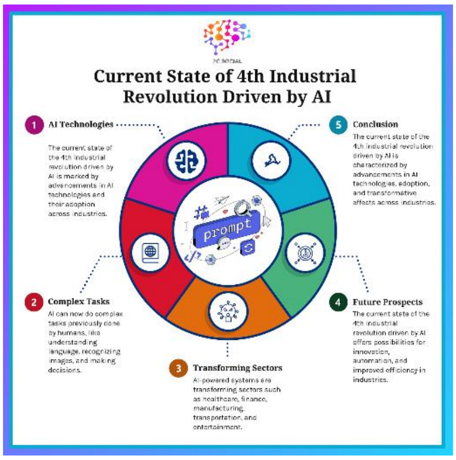

Fig 2. Artificial Intelligence Is Transforming the Business World
(Source: Pcsocial, 2025)

The shortcomings of the models of fixed compensation are numerous. They tend to continue any already existing pay disparities, since initial proposals and future increases can be affected by unconscious bias. They react slowly to the market value of individual skills changing on a real time basis resulting in the employee being either grossly overpaid or

worse still underpaid and at the risk of high attrition (Kurpicz-Briki *et al.,* 2024). Moreover, they make employees a homogenous group, not considering the personalized preferences on what constitutes their total rewards, whether it be, a higher base salary, share options, flexible working schedules, and learning and development budgets.
The advent of Artificial Intelligence (AI) as a disruptive business phenomenon creates an unparalleled chance to rethink the practice of compensation of the workforce. Machine learning (ML), and predictive analytics are a subset of AI, which is capable of analysing large and complex data sets to reveal trends and insights unattainable by humans. This is what allows the shift of the stagnant to the dynamic tariff plans. A dynamic tariff plan refers to an adjustable, data-driven compensation scheme which naturally adapts to the variety of internal and external influences. It may do this by personalizing the offers to new candidates, prescribing merit-based increases and bonuses using predictive performance and retention models, as well as continually comparing the internal compensation with up-to-date market data.
The following paper is intended to present an in-depth discussion of AI-based decision-making when it comes to designing and managing dynamic tariff schemes to compensate employees. It will start with literature review of the development of the compensation theory and the new research on AI in HRM (Christensen *et al.,* 2023). This research will have a methodology part that will describe a conceptual framework of how the elements of an AI-driven compensation system should be understood. After that, the application of AI to different compensation issues is going to be broken down into a detailed analysis, and the implications of the topic (ethical, practical, and strategic) will be significant. The conclusion will summarize the results and suggest a way forward on the way of organizations interested in using AI to make their compensation strategy more agile, fair, and efficient.

Literature Review:
Theory and Practice of Compensation Evolution.
The traditional compensation theory has its basis in the equity, expectancy and agency theories. Equity theory (Adams, 1965) is the assumption that employees desire that there is a just balance between inputs (effort, skill, experience) and outputs (salary, benefits) of the employees to others.

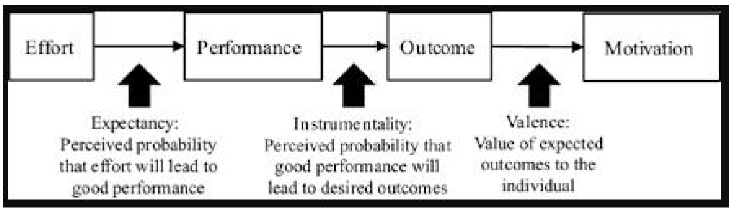

Fig 3. Vroom expectancy theory
(Source: Researchgate, 2025)

According to the expectancy theory (Vroom, 1964), motivation is a propensity of the perception that performance will be achieved by effort, and the performance will result in a desired reward. The agency theory (Jensen and Meckling, 1976) focuses on the conflict of interest between principals (owners) and agents (employees) and his argument in support in line with compensation structures that are more aligned with organizational goals over those of the employees.
These theories have been put in operation using Hay Guide Chart-Profile Method, broadbanding and competency based pay structures. These systems, though advanced in their time, are based on periodical job appraisals and market pricing drills, the latter being usually

held once a year in the form of third-party surveys. This induces a considerable time gap, which makes the data outdated in some way before it is put into practice (Pavlopoulos *et al.,* 2024). It has been recognized in the literature that fixed nature of these systems has been a constraint especially in knowledge based industries whereby the value of particular skills may be valued within a short period of time (Kalusivalingam *et al.,* 2022).

The Strategic Compensation and Total Rewards Advent

The idea of strategic compensation was introduced and believed in balancing the pay practices with business strategy (Yanamala, 2023). This has become the Total Rewards model that allocates a broader definition of compensation to encompass not only monetary components (base pay, variable pay, stock) but also benefits, work-life balance, performance recognition, and development opportunities (Adeusi *et al.,* 2022). The Total Rewards policy focuses on customization, but has proven challenging to scale up because of the bureaucratic complexity of packages being customized to cover thousands of employees. The gap found by the literature is the difference between the theoretical attractiveness of the personalized total rewards and the actual tools that the HR departments can use to make it a reality.

AI in HRM: The Nascent Wave

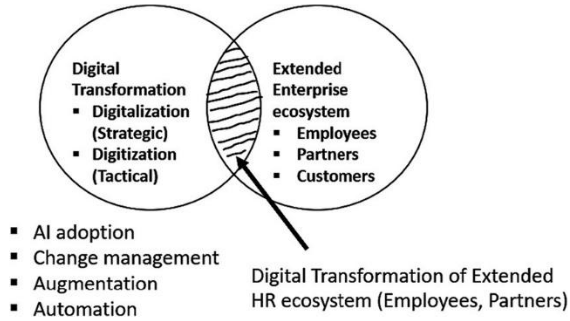

Fig 4. AI in HRM
(Source: Singh and Pandey, 2024)

People Analytics (also known as HR Analytics) is a fast-expanding academic and practical topic, the application of AI in HRM. First studies have paid much attention to the field of talent acquisition, and AI-powered systems are applied to resume screening, source a candidate, and initial interaction with a chatbot (Daneshjou *et al.,* 2021). Research has revealed the benefits of efficiency of these recruitment tools and the risks of algorithmic bias (Singh and Pandey, 2024).

The use of AI in compensation is also less well-documented, but it is considered to be one of the fronts. Researchers have also started to understand how predictive models can be used in predicting employee turnover which is one of the major variables during compensation decisions (Paulus, 2023). The application of ML to internal pay data to detect and address gender- or race-based pay gaps has been studied in other studies (Geissbühler *et al.,* 2021). The general theme of the literature is that AI can transform HR into a responsive, administrative role to a proactive, predictive, and strategic ally. Nevertheless, there is a lack of a holistic approach to the way AI can be implemented in a systematic manner to design and operate dynamic and personalized tariff plans, which the given paper aims to fill.

Methodology:

In this study, the empirical research design that is employed is based on secondary data to examine how AI can be used and the results of its use in compensation management. The goal will be to cease the intellectual constructs and examine real, practical data to determine patterns, correlations and indication of effectiveness or confrontation.

The research methodology focused on the gathering and quantitative and qualitative research of the existing datasets and reports. The three primary groups of information were used: (1) Publicly Available Industry Benchmarks: Aggregated and anonymized compensation information in the form of platforms was examined to monitor the dynamism of skill-based pay premiums over 24 months, which serves as a reference to the dynamism of market conditions. (2) Published Case Studies and White Papers: Detailed implementation reports of HR technology vendors and consultancie were searched through (Moffit *et al.,*2022). These documents were coded on main variables, such as reported outcomes on pay equity (e.g. reduced adjusted pay gaps), retention rates among employees before and after the implementation and the adoption measures by managerial personnel. (3) Academic and Regulatory Datasets: Secondary data analysis was carried out using academic research on algorithmic bias and published regulatory results on the subject of discrimination in automated pay and hiring systems.

The analysis was both descriptive (to summarize trends e.g. the percentage change in companies using predictive analytics to make merit increases) and thematic (to determine common challenges and challenges and common success factors throughout the qualitative case studies). This can be done in an empirical method whereby the current performance of AI-driven tariff plans can be evaluated based on the reported experiences of organizations that pioneered the use of the technology instead of theoretical speculation.

Analysis:

A dynamic tariff plan based on AI is not a tool, but a system. Its design may be separated into four fundamental units, including Data Aggregation, Predictive Analytics Engine, Decision Support Interface, and the Feedback Loop.

Aggregation and Process of Data

The basis of any AI system is data. In the case of dynamic compensation, this includes the aggregation and structuring of data by a number of, disparate sources:

Internal Data: It contains HRIS data (salaries, job history, tenure), performance management data (quantitative and peer-review and 360-degree feedback), learning/development data (learned skills, certifications obtained, employee engagement survey), and employee engagement survey data (Singh and Pandey, 2024).

External Data: This is essential in benchmarking in real-time. AI platforms are able to scrape and consume data posted online in job advertising platforms (e.g., LinkedIn, Indeed) to calculate the market rate of individual skills and positions in particular geographies. They may also be in combination with special compensation information providers (e.g., Payscale, Radford) and macroeconomic indices (e.g., inflation rates, cost-of-living indices).

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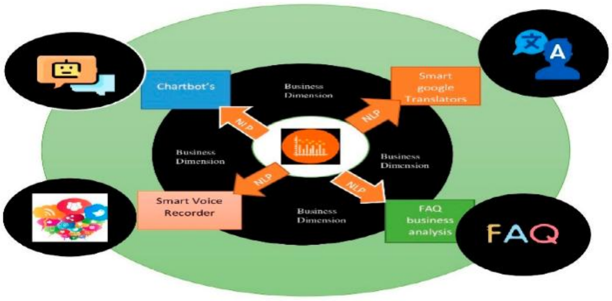

Fig 5. Advanced Natural Language Processing (NLP) in HRM
(Source: Mah *et al.,* 2022)

Unstructured Data: Advanced Natural Language Processing (NLP) may read unstructured information, e.g. project feedback, internal messaging and even transcript of an exit interview, to understand the impact that an employee makes, their ability to collaborate and the real cause of the dissatisfaction (Sanni, 2023).
This information is then washed, standardized and transformed to a single ontology- a model of skills, competencies and roles. This enables the system to comprehend that the same skill is represented by, amongst others, Python programming, coding in Python, and Python development so that the same can be compared and valued.

The Predictive Analytics Engine
This forms the main brain of the system, where machine learning models of the aggregated data are applied. There are numerous important models that are collaborative:
Skills Valuation Model: The model is in a constant analysis of the external market data in order to identify the real-time value of the organization economic value of each skill and the combination of the skills in the organizational ontology. It is able to recognize the so-called premium skills that are demanded but scarce and provide specific premium compensation.

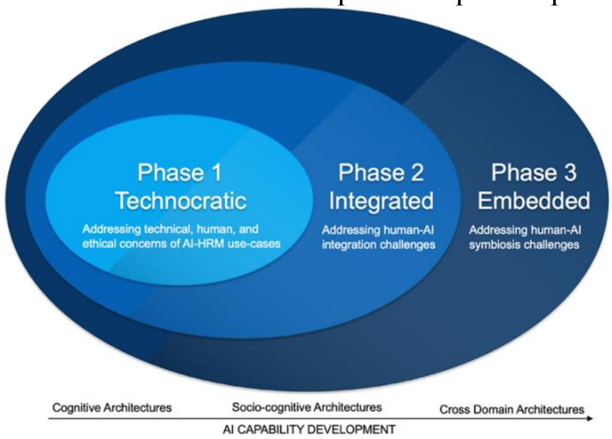

Fig 6. The role of HRM in humanizing AI in the workplace
(Source: Fenwick *et al.,* 2024)

Flight Risk Prediction Model: The ML model can predict the probability of flight risk in individual current employees by learning how other employees who have already left the company have performed over time (e.g., tenure, performance history, salary relative to market, engagement score, frequency of profile updates on LinkedIn, etc.) and assigning a probability of flight risk (Fenwick *et al.,* 2024). This is a paramount input towards retention-oriented compensation modifications.

Performance Prediction Model: It takes performance data of the past, the results of the project and even feedback trends of peers of an employee to anticipate future performance and potential of a worker (Zharova, 2023). This aids in distributing the variable pay and the high potential employees to receive long-term incentives.
Pay Equity Analysis Model: This is a model that conducts ongoing audits of the pay data of the organization. It balances legitimate variables such as role, experience, performance and location in order to find out unexplained pay differences that may be due to gender, racial or other forms of prejudices. It is able to proactively identify outliers that can be reviewed by the managers.

Decision Support Interface
The AI system does not usually take independent decisions on compensation (a practice that is highly risky both in legal and ethical aspects). It, instead, gives strong, and customized recommendations to managers and HR business partners via a user-friendly dashboard (Sanni, 2023).
To the Hiring Managers: The system will be able to suggest a tailor-made and competitive pay package when making an offer. It would show the range of market values the candidate is worth, propose a starting pay and even offer a combination of base, bonuses and equity that is both cost efficient and attractive to the candidate, using the data of the other successful offers of the same type.
In the case of Performance and Merit Cycles: In lieu of the homogenous budget pool, the individual team member raise and budgetary recommendations are available to the managers through the system (Zharova, 2023). Such recommendations would be made with a weighted algorithm based on the prediction of individual performance, compa-ratio (ratio of salary to market midpoint) and flight risk and the essentiality of skills.
In case of Total Rewards Personalization: The system would provide employees with a menu of rewards. It can push employees towards the decisions that give them the greatest perceived value, based on data on their preferences (implied or stated, e.g., suggesting more vacation days instead of a small salary increase to an employee who highly values work-life balance).

The Continuous Learning and Feedback Loop
An actual AI system is self-educating. What its recommendations yielded a candidate did take an offer, did an employee who was granted a raise thereafter exhibit less flight risk, the predictive models ingest the outcomes of its recommendations, and the association between a particular mix of rewards and an employee engagement (Lee and Kim, 2023). This is a continuous feedback loop which makes the models more accurate and specific to the context and strategic objectives of the organization.

Empirical Evaluation
A dynamic tariff plan based on AI acts as a combined system, through which various data is transformed into practical compensation information (White *et al.,* 2022). The architecture of it has four basic blocks, and it has mathematical models which form the analytical basis thereof.
Dealing with Data Aggregation and Processing.
The system takes in systematized and unsystematised data in internal HR systems, external job markets and macroeconomic data. One of the most essential steps is to map such data to a common skills ontology to standardize the different names (e.g., "Python programming" vs. "codes in Python") and be able to analyse them correctly.

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The Predictive Analytics Engine

Here the machine learning models operationalize the data. The most important models can be represented in form of equations that control their rationale.

Flight Risk Prediction: It is possible to estimate the likelihood of employee leakage using a logistic regression model. The model might weigh factors such as:

$$P(Turnover) = 1 \ / \ (1 + e\hat{}(-z))$$

Where

$$z = \beta_0 + \beta_1 * (Compa - Ratio) + \beta_2 * (Engagement\_Score) + \beta_3 * (Time\_Since\_Promotion) + \ldots$$

In this case, the coefficients (β) are trained by using past data of former departed employees.

Skills Valuation Model: This model calculates the premium of a skill in the real time market. A simplified representation is a multivariate analysis:

$$Skill\ Premium = \alpha + \theta_1 * (Market\_Demand) + \theta_2 * (Skill\_Scarcity) + \theta_3 * (Strategic\_Value)$$

Theta (θ) coefficients quantify how much each factor (demand, scarcity, etc.) contributes to the skill's financial value.

Pay Equity Audit: This type of model detects pay gaps that cannot be explained. One of the common methods is a linear regression which can be used to anticipate the salary of an employee based on the valid aspects:

$$Predicted\ Salary = \gamma_0 + \gamma_1 * (Years\_Experience) + \gamma_2 * (Performance\_Rating) + \gamma_3 * (Job\_Grade)$$

The existence of a significant (systematic) residual (the difference between actual and predicted salary) of a demographic group may reflect an equity concern.

Table 1: Input Variables for Predictive Models

Model	Key Input Variables
Flight Risk	Compa-Ratio, tenure, promotion history, engagement score, peer connectivity, recent skill growth.
Skills Valuation	Job posting frequency for skill, salary mentions in postings, certification costs, internal project demand.
Performance Prediction	Historical performance ratings, project completion rate, 360-feedback sentiment, new skill acquisition rate.

(Source: Self-developed)

Decision Support Interface & Feedback Loop

The engine outputs are made in the form of recommendations, but not independent decisions. An example is the merit increase recommendation that could be a weighted weight of multiple scores:

$$Raise\ Recommendation = (Performance\_Score * \ W\_perf) + (Flight\_Risk\_Score * \ W\_risk) + (Skill\_Prem$$

W are weights established by organizational strategy (e.g. a retention based firm would have a large W risk). The results of these decisions (e.g. is the employee remaining) are fed into the models and this generates a continuous learning loop that makes the future prediction more accurate.

Table 2: Illustrative AI-Generated Compensation Recommendation

Employee Factor	Score	Market/Internal Data	AI Recommendation

Current Base Salary	-	$95,000	-
Market Median (Role)	-	$105,000	Alert: Below Market
Performance Prediction	8.5/10	Top 15%	-
Flight Risk Probability	78%	High Risk	Priority for Retention
Critical Skill Premium	-	+$8,000	-
Recommended Adjustment	-	-	Base Increase: $12,000 + Retention Bonus: $5,000

(Source: Self-developed)

Therefore, AI transforms administrative tariff strategies that are strategic and dynamic into dynamic and strategic tools. It is a four-component architecture, where data aggregation of internal and external sources is combined with a predictive analytics engine, which is powered by skills valuation and flight risk and pay equity models, a decision-support interface, which provides managers with advice based on data, and a feedback mechanism to permit continuous learning. These systems permit a customized and fair compensation determination and real-time responsive choices by taking advantage of formulas and actual time information. They satisfy the compensation management by redirecting it to proactive retention, simplified budgetary allocation and reduction of bias which ultimately are agile and competitive in the talent war.

Discussion:

Presenting the AI-powered dynamic tariff plans has dramatic impacts at the organizational level and employee level and HR profession in general. The benefits far outweigh the challenges as discussed in this discussion.

The advantages of AI-based dynamic compensations

Improved Pay Equity and Bias Removal: With the help of data-driven algorithms that adjust to objective variables, companies can be able to detect and amend pay inequity in a structured manner. Although a subject to bias, a properly designed AI system can be more predictable and open compared to the subjective and opaque choices of individual managers (Miani, 2022).

Better talent retention: The capacity to forecast flight risk and actively provide market consistent changes or retention bonuses is an effective weapon (Kambur and Yildirim, 2023). It changes compensation as a reactive cost (counter-offers) into a proactive contribution to critical talent retention.

Optimized Compensation Budget: AI can be used to allocate the compensation budget in a more strategic manner. Funds can be allocated to high-performs, employees with key skills and those at risk of being attracted away, instead of across the boards and the impact of every dollar can be maximized.

Heightened Velocity and Competitiveness: The dynamic plans enable the organizations to act in almost real-time to market changes. When one of the AI engineering skills is over- or under-valued, the company can adapt the corresponding pay scales instantly, which means that the company will not lose out on the talent (Dhiman,2 024).

Personalization and Employee Empowerment: Providing employees with insight into the manner in which their compensation is calculated, as well as allowing them to customize their total rewards, makes them feel valued and fairly treated (Rachid and Houda, 2024). This will be a major work boosting and satisfying.

Important Issues and Moral Implications

Algorithmic Bias: The biggest danger is that AI systems will reinforce or even increase the already existing human passions. When the historical pay data is biased (i.e. underpayment of women), the model that is trained on such data will have learned to follow the same pattern in the future. The saying that garbage in, garbage out applies very critically. This can be mitigated by close auditing, application of de-biasing methods and use of various data sets.

The Black Box Issue: A lot of advanced ML models, and especially deep learning networks are opaque. It might not be easy to realize why the model had to recommend a certain thing (Kaaria, 2024). Such unaccountability is a huge obstacle both to employee confidence and legal conformity, particularly when a worker appeals against a compensation determination.

Data Privacy and Security: AI compensation system must have access to a large pool of sensitive employee information. The most important thing is to be sure that this data is gathered in an ethical way using secure storage and it is utilized in accordance with such regulations as GDPR. The employees should be enabled to understand the use of their data and have transparency and control over it.

Dehumanization of HR: Excessive use of AI may lead to the loss of human touch to a set of algorithmically-accepted deals. The delicate background of employee situation, individual issues, group dynamics, career goals can be forgotten (Fewick *et al.,*2024). This will lead to the loss of the work force and culture of the organization.

Managerial Deskilling and Resistance: By simply signing AI recommendations, managers will lose the fine art of achieving tricky compensation deals and making judgmental decisions based on human beings. In addition, the reduction of autonomy and discretion of the managers who are to be subjected to such a system is likely to be opposed by the managers.

Difficulty of Implementation and Governance: Stabilizing such a system, developing it, and supporting it is a burdensome undertaking technologically, in data infrastructure, and expert skills (data scientists, AI ethicists). There must be a well-defined governance structure to manage the models, deal with exceptions and carry out the change process.

Thus, one of the most vital dualities of AI-driven compensation implementation is the promise expressed. The positive results are significant: pay equity by identifying the bias, better retention due to the predictive analytics, and cost allocation efficiency. Nevertheless, there are still great difficulties. Algorithms will be the biggest threat when trained on invalid historical data that will continue to perpetuate discrimination. The fact that some AI is a black box may destroy trust and transparency, and large volumes of data may be the source of serious privacy issues. The difference between success and failure lies in striking a balance between human-in-the-loop solution, where AI is suggested, but the HR professionals and managers, who provide ethical oversight, understanding of the context, and the vital aspect of a fair pay.

Conclusion:

Artificial Intelligence-driven transformation of the non-dynamism back to the application of the dynamic tariff plans is a historical change in the philosophy and reality of the compensation of the workforce. The conventional model with its yearly cycles and standardized methods does not match the dynamics, skills-based and individual world of work. AI provides the means to create a more reactive, fair, and functional system that would help to correspond employee value and market reality and organizational strategy in real-time.

The discussion above confirms that AI may be used to promote pay equity by continuous auditing, enhance retention by flight risk models, and manage compensation expenditure by investing in areas where it is most likely to be effective. Technologically, but also strategically, a structure of such a system employing an integrated data foundation, predictive analytics, and intelligent decision support is not only possible, but also compelling.
This, however, is a risky ride. The risk of algorithmic bias, violation of data privacy, and dehumanization of the workplace is not an issue in the virtual world. They cannot be a post-hoc. In this new frontier, technology will not be the success factor. It will be based on its judicious use.

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