



Facultad de Ciencias Económicas y Empresariales
ICADE

**EXPLORING THE USE OF ARTIFICIAL
INTELLIGENCE IN HUMAN
RESOURCE MANAGEMENT ACROSS
THE EMPLOYEE LIFECYCLE: A
QUALITATIVE STUDY OF THE
BANKING INDUSTRY**

Autor: Jamie Christopher Ivory
Director: María Jesús Belizón Cebada

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1. ABSTRACT & KEYWORDS

This study investigates the current and emerging role of artificial intelligence across the human resource management lifecycle within the banking industry. Despite growing academic interest in AI-driven HRM, empirical research examining its practical application across multiple HR functions remains limited. With a qualitative approach, six semi-structured interviews were conducted with HR practitioners specialising in recruitment and selection, learning and development, compensation, and AI governance, all within one of the world's largest multinational banks. Findings reveal that AI adoption across the HR lifecycle is concentrated primarily in the automation of administrative and repetitive tasks, with tangible efficiency gains evidenced across multiple functions. While AI is broadly embedded as a productivity and content generation tool, its role in strategic decision-making remains limited, with practitioners consistently positioning AI as a decision-support mechanism rather than a decision-maker. Governance frameworks, data confidentiality constraints, and the EU AI Act emerge as structural moderators of AI's decision-making potential. The study concludes that human judgement remains irreplaceable in high-stakes HR decisions, and that the extent of AI integration varies considerably across HR lifecycle stages.

Keywords: Artificial Intelligence, Human Resource Management, HR Lifecycle, Banking Industry, Automation, Decision-Making, AI Governance, Learning and Development, Recruitment, Compensation

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3. INTRODUCTION

Artificial Intelligence (AI) has taken the world by storm in recent years, and its use in organisations is growing at an exponential rate. It now has a large influence on how decisions are made and acted upon in all areas of businesses across the globe. As a result of the speed at which AI has developed, there has been a limited amount of research conducted on how AI is being applied in human resource management (HRM). Little is truly known about just how much of the human resources (HR) lifecycle has been effectively automated through the use of AI, and the areas in particular where human judgement remains crucial.

The aim of this research project is to find out the extent to which HRM practices can now be performed using AI tools, and how much human oversight is still needed to make its use effective in organisations. The project focuses particularly on the banking industry. Due to the data-heavy nature of the industry, it has been consistently at the forefront of digital transformation, with many banks pioneering digital innovation through AI adoption. This study examines how AI is implemented by HR teams across the employee lifecycle in this industry.

The general objective of this project is to understand how AI is used in HRM across the employee lifecycle in the banking industry, and to examine the balance between automation and human judgement. The objective seeks to answer the following research questions:

- I. What are the current concrete uses of AI across the different stages of the HR lifecycle in the banking industry?
- II. To what extent does the use of AI automate the processes involved in the different stages of the HR lifecycle in the banking industry?
- III. To what extent does the use of AI-driven insights enhance decision-making throughout the different stages of the HR lifecycle in the banking industry?

To answer these questions, secondary research in the form of a review of academic literature, company reports, and consultancy reports provides the theoretical context. This is followed by primary research in the form of qualitative semi-structured interviews with HR professionals working in one of the world's largest multinational banks, offering a first-hand perspective on the practical reality of AI in HRM.

4. LITERATURE REVIEW

To begin to understand the applications of AI in HRM in the banking industry, it is imperative to not only understand what HRM actually is, but also to break it down into stages, to uncover the concrete uses in each stage, and measure just how much influence it has on decision-making. The concept of HRM has changed and evolved over the course of many years, and while there are many variations of its definition, an appropriate contemporary definition is that it concerns the policies, practices and strategies that organizations adopt in order to manage their employees and the employment relationship itself (Wilkinson et al., 2024).

Breaking down HRM into various components allows for it to be analysed in greater detail, with a suitable manner to compartmentalize HRM being through the use of the employee lifecycle. This is a model that divides the journey of a theoretical employee through their employment with an organization, from recruitment, all the way through to separation. Once again there have been various adaptations of this model throughout recent years, each defining different stages in the cycle. Some models break it down into as many as 12 stages, with others opting for a simplified version of as few as 4 (Gladka et al., 2022). After careful consideration and review of the various models, it is clear that there are some stages with which the majority of the academics that have covered this model can agree upon, which are as follows:

1. Recruitment & Selection
2. Learning & Development (L&D)
3. Performance Management
4. Compensation

HRM is extensive and complex, and for this reason analysing all possible applications of AI in HRM would be an exhaustive task. However, by dividing HRM into the components above, it allows for each part to be analysed and researched in depth, to understand the precise applications of AI in HRM. It can also be understood that it would be impractical to conduct a review of literature that is solely based on the banking industry. For this reason, the review will be conducted on HRM in general, across all industries, with a banking specific focus to follow in the qualitative research. The following is an in-depth analysis of each of the 4 chosen parts of the employee lifecycle, outlining the uses of AI in automating HR processes, and also how

it can influence decision-making. There will also be an additional section to explore other, more general use cases that lie outside of these 4 stages.

4.1 AI in Recruitment & Selection

Recruitment and selection represents the beginning of the employee lifecycle, and it encompasses the very first interactions that employees have with their employer. Recruitment is defined as the process of carrying out activities to not only identify but also attract potential employees to an organisation. This differs from selection, which is the next step in the process concerned with selecting the most appropriate candidate to fill a vacancy (Torrington et al., 2020). These seem like simple tasks, but in reality, it can be difficult to find and employ the right people, as is pointed out by Stephen Bach when he wrote that recruiting and selecting employees is essentially trying to predict the future. It involves making predictions about the future behaviour of individuals once they are employed. Bach also emphasises that unfortunately it is not possible to predict the future, making this part of the employee lifecycle more about probability and informed judgment (Bach, 2009). Thankfully for HR professionals the increased use of technology in HRM is making these predictions more efficient and effective. Often referred to as “e-HRM”, technology has been heavily influencing HR processes since the turn of the century, particularly in the areas of recruitment and selection (Stone et al., 2015). The introduction of AI can be seen as the next step in this evolution.

While the possibilities that can be unlocked through the use of AI in HRM are endless, recruitment and selection is perhaps the area that holds the most potential. A 2024 survey of chief HR officers conducted by the Boston Consulting Group found that 70% of the experimentation with AI in companies is done in HR, and that talent acquisition is the top use case within this. This is due to AI’s strong marketing and administrative capabilities, with these types of tasks forming a key part of this phase of the employee lifecycle (BCG, 2025).

There is no doubt that AI can massively boost productivity in this area, however there are also some issues and concerns regarding its use to identify and attract candidates. Global recruitment consultant Morgan McKinley demonstrate in their 2025 Global Workplace Trends

Survey that despite the fact that 54.42% of respondents believe that AI has a positive impact on recruitment, 6.12% disagree, with 39.46% being unsure (Morgan McKinley, 2025). These concerns, which relate to fairness and ethics, stem from the inherent biases that AI models can possess, which can lead to unethical recruitment decisions being made unconsciously. The combination of both potential and concern makes navigating the use of AI in recruitment and selection both intriguing and challenging, which can be clearly seen in the following use cases within recruitment & selection.

The banking industry is one of the most prestigious and well-respected industries in the financial services world, with this being reflected clearly in the volume of job applications received by banks around the world. To put this demand into perspective, in 2025 JPMorgan received 630,000 applications for internships (Financial News London, 2025). These figures demonstrate the sheer quantity of applications that large Wall Street banks receive for job openings. To cope with this volume companies have had to innovate, as it is not feasible for humans to review each and every CV received for vacancies, and for many years now AI has been the answer.

Machine learning algorithms and natural language processing models can be used to automatically screen thousands of CVs to identify the most appropriate candidates. These models are trained on large datasets of CVs to identify what traits a desirable employee has for a role (Albassam, 2023). These AI models have been found to reduce manual efforts by 80%, leading to massive time savings for recruiters (Ujlayan et al., 2024).

Despite the increased efficiency and productivity achieved through the use of AI CV screening, the ethical concerns surrounding its use, and in particular ethical training of the models are highly documented in the academic literature on this tool. The AI systems applied in these areas can sometimes hold biases that it picks up from the training data (Hunkenschroer & Luetge, 2022). If there is a lack of diversity in the data given to the model, e.g. a lack of a certain gender, race, or other characteristics, the model will be predisposed not to recommend people who display these characteristics in their CV. This phenomenon may ultimately lead to a less diverse workforce. There are many benefits associated with a more diverse workforce,

such as not only enhanced creativity, innovation, and problem solving, but also a greater connection to clients (O'Brien et al., 2015). For this reason, it is imperative that companies ensure that the utmost is done to ensure the AI systems are free from bias.

Job interviews are a milestone part of the recruitment process and often represent the first truly tangible interaction an employee has with their employer. While they are a necessary step, it cannot be denied that carrying out interviews is highly time consuming, especially when interviewing multiple candidates. This increases further when considering recent trends of conducting multiple rounds of interviews with each candidate, or panel interviews where multiple people from the company attend the interview. For this exact reason there has been a recent emergence of automated job interview specialists such as Hirevue, who claim a 90% reduction in time to hire through the use of their innovative AI recruitment solutions (Hirevue, 2026).

Hirevue AI interviews are widely applied, particularly in the banking industry. Hirevue allows companies to use AI to analyse video interviews, assessing both verbal cues and nonverbal cues, including choice of words and tone. Their machine learning algorithm which is trained on data from previous interviews ultimately gives each candidate a rating on a variety of desirable features for candidates (Zhou, 2024). Ultimately the hiring decision is still in the hands of humans, however, it is highly based upon the work of AI. AI models can often contain any biases from its training, e.g. prejudice against a particular race or gender. One particular academic study conducted by the New York University Center for Bioethics suggests that such biases are particularly strong against people with disabilities, stating that data scientists need to tackle the issue to stop the exclusion of marginalised communities from employment opportunities (Tilmes, 2022). The use of flawed AI models tarnishes the human's ability to make ethical decisions using the data and raises grave ethical concerns about the use of AI in recruitment & selection.

While it is undeniable that conducting this type of interview can save HR professionals a large amount of time, and allow for increased productivity, there are questions regarding the perception of the use of AI interviews amongst candidates, and how it portrays companies that

are using them. A very important part of a job interview is the personal connection that is derived from genuine human interaction, something that is quite obviously not achieved through AI interviews. There is a risk that this may cause candidates to feel like they are being treated impersonally and can reduce candidates to feeling like “just a number”, or that they are not valued enough to merit being interviewed by an actual person (Acikgoz et al., 2020).

While the two previous examples of use cases of AI in recruiting involve complex AI models, that involve training algorithms and machine learning, not all uses of AI to recruit the right people have to be so complicated and hard to implement. Perhaps the most simple and obvious possible use of AI in recruiting is the use of generative AI to write job descriptions. Writing an effective job description may be more difficult than it appears, with one study showing less than 40% of candidates find them comprehensible (Qin et al., 2023). Tools such as ChatGPT can be used to produce content that is not only creative but also reads as if it were produced by a human (Walker & Larson, 2025). While in this use case the AI can give suggestions, ultimately the decision still lies entirely within the hands of the human.

4.2 AI in Learning & Development

After a company successfully identifies suitable employees, and selects the right one for the job, L&D is the next step in the cycle that aims to make employees more competent and increase their performance. Similarly to recruitment and selection, learning and development are often used as synonyms, but they are two separate processes. Learning is the process of providing employees with knowledge that will make them more efficient at their current job. Development on the other hand has a more long-term focus, preparing employees for potential future roles (Martocchio, 2019).

The AI revolution itself is the perfect example of the importance of the L&D function of the employee lifecycle within HRM. In just a few years AI has become one of the biggest talking points in thousands of businesses across the world. AI is now integral to the way many companies operate, and as such there is a growing demand for employees to be AI literate, having enough knowledge about how to use AI to leverage its capabilities for the benefit of the

company. For this reason, it is now common practice for firms to upskill their employees in AI, providing them with adequate training to increase their AI literacy (Benlian & Pinski, 2025). This shows the need for L&D professionals to stay on top of trends and provide employees with the highest quality training as possible, and leveraging AI is certainly a method that is being used to achieve this. Like in most sectors, in recent years there have been major advances in the use of AI in education in general, with one study suggesting that 60% of public-school teachers in the United States are using AI in their teaching (Youngstown State University, 2025). Meanwhile UNESCO estimate that over two thirds of third level education institutes are developing frameworks to manage the use of AI within education (UNESCO, 2025). This trend is now also being implemented by HR teams within organisations, seeking to enhance the learning experience for their employees.

The use of AI has allowed for a learning experience within organisations that is more personalized than ever previously possible. Organizations can now implement learning management systems for their employees to use, that are powered by AI and machine learning. These advanced algorithms can analyse individual employee profiles and recommend them learning paths that are tailored to their needs. One example of this system is the Degreed learning platform, which has been implemented by companies around the world to great effect (Khamis, 2024). This type of system greatly enhances the individual learning experience, ensuring that employees are using their learning time efficiently to pick up new skills that will be applicable for them in their roles. This has even shown to lead to an increase in employee retention in comparison to using more traditional methods (Madhumithaa et al., 2025).

AI is also being used to generate the learning content itself. Through the use of natural language processing and natural language generation, AI can automatically produce additional material, to complement the already existing learning pathways or materials, such as automatically generated overviews and reflection quizzes (Diwan et al., 2023). These features can easily enhance the learning experience by providing dynamic content that is adaptive to each user. It also provides the ability to automate manual tasks. In the example of the reflection quizzes, generative AI can generate a large pool of questions instantly, that provides variety for users, something that would have previously been highly time consuming.

Similarly to its use in recruitment and selection, ensuring that AI systems implemented across L&D align with ethical standards is of paramount importance. In particular, in any situation where an AI is making learning recommendations to employees, the models behind these recommendations must be monitored closely to ensure they do not contain biases (R. N. R. Nyathani, 2023). These models are generally built on historical learning and performance data, which may limit development by reinforcing current skills. It is imperative that the data sets that such models are trained on are free from any biases that may lead to unfair learning recommendations.

The continuous theme that can be noted from the literature on AI in L&D is increased levels of personalisation for learners, but we must also recognise the continued importance of human oversight in relation to these systems. In the more complex use cases, in particular in the case of AI-powered learning management systems, the role and influence of AI is far greater. The systems can entirely shape each employee's learning experience by recommending content to improve priority skills. This leads to a growing reliance on assuming that these AI systems are operating fairly and accurately. Ultimately, in order for the implementation of AI within L&D to be a success, organisations must keep an appropriate balance between innovation and human judgement.

4.3 AI in Performance Management

After employees have been selected and trained, it is important for companies to be able to gauge if they are fulfilling their role successfully. This is achieved through a phase of the employee lifecycle known as performance management. It can be described as a continuous cycle of communication between managers and employees, that ensures that the employee is contributing towards the goals of the organisation. It consists of laying down what is expected of the employee, fixing measurable objectives, giving progress updates, and finally evaluating outcomes (University of California, Berkley, 2026).

In the Deloitte 2025 Global Human Capital Trends survey, an annual research report by the world's largest professional services network, performance management was described as an

area that is disliked by both managers and employees, stating that there is a lack of trust in the process. However, the report highlighted how AI has the potential to alter this view of performance management by making it simple (Deloitte, 2025).

One study in this area looks into the integration of AI into performance management systems, capable of automating and enhancing the length and breadth of the performance management process within organisations. Here we see once again the capability that AI has to analyse large amounts of data, with the systems being able to analyse performance data to produce actionable insights (Varma et al., 2024). The upsides to this are positive, however once again ethical concerns arise. These AI models must be monitored closely, as the output they produce could be used to make decisions that have a significant impact on the lives of employees. In particular, with any serious decisions surrounding relieving an employee of their duties, there must be a degree of certainty that perhaps is not guaranteed by AI.

One specific area of performance management where we have begun to see the implementation of AI is in goal setting, where it has slowly been replacing traditional goal setting systems. Previous approaches are considered to be very rigid and inflexible, as goals were often set annually by more senior managers. Through the application of AI goal setting has now become a highly personalised experience for employees, as AI algorithms can help to suggest goals based on historical data such as previous performance, skills, and role requirements. AI is able to continuously monitor goals and provide real-time feedback and insights, while also providing the ability for goals to be dynamically adjusted depending on evolving business conditions (Febiula et al., 2025). Not only does this automate manual tasks, saving time and allowing for timely data-driven decision-making, but it also creates a more engaging experience for employees.

A highly plausible reason for the lack of trust in performance management that was highlighted in the aforementioned Deloitte report is the heavy influence of bias on traditional performance appraisal processes. Traditional performance appraisals conducted by team managers are often heavily influenced by a range of biases, e.g. recency bias or favouritism. AI-powered performance management replaces this entirely, as subjective reviews are substituted for ongoing

appraisal based on objective performance data (R. Nyathani, 2023). This promotes an environment of trust, transparency, and meritocracy, where employees are assessed based on how well they perform their role, as well as reducing inequality and potential for discrimination. AI not only automates the appraisal process, but also helps HR professionals make better, fairer decisions.

One thing that is very apparent is the limited volume of literature available in the realm of performance management in comparison to the previous two sections, which illustrates that it is more of an emerging application of AI within HRM. One potential reason for this is the fact that performance management is inherently more personal and human in nature. This is because performance management involves judgement and taking decisions that can significantly impact an employee's career progression and life. The existing research does highlight promising use cases, particularly in goal setting and appraisals, however it also once again raises ethical concerns relating to the use of AI in important decisions, highlighting the continued importance of human oversight.

4.4 AI in Compensation

The term compensation in the context of the employee lifecycle, which is also often dubbed pay and rewards, refers to the process of a company remunerating employees in return for their work towards the furtherment of the firm. This not only covers their basic salary, but also other elements such as commissions, bonuses, and any type of benefit in kind including health insurance, pension plans, and paid time off (Reddy, 2025). It is a pivotal stage in the employee lifecycle as it directly influences motivation levels, which in turn is closely tied to employee performance. It is also true that compensation has a substantial impact on the recruitment and selection process, as a more optimal compensation package allows a company to attract better talent. This function is paramount to HRM, and for this reason it is important to drive efficiencies, such as through the use of AI.

Despite the obvious importance of compensation in the employee lifecycle, arguably having the greatest impact of all sections on the employee, historically there has been a lack of research

in this area. One study which reviewed over three decades of compensation research highlighted the blurry relationship between pay and actual performance. This is due to the fact that pay is comprised of many factors, such as pay transparency and pay dispersion, which all impact employee performance (Fulmer et al., 2023). This lack of research shows why the implementation of AI into compensation is significantly complex, as compensation decisions are already extremely complex in themselves.

The lack of general research in compensation may also explain why there is limited further research into AI in compensation. Taking into account the three sections of the employee lifecycle previously covered in this literature review, compensation is without a doubt the area with the least amount of material to cover. Much of the existing literature frames the use of AI more as a prospect for the future, rather than something that is being extensively deployed by HR teams in the present moment. There are suggestions that the application of AI in compensation is the solution to overcome the current challenges, such as changing market conditions and evolving regulatory requirements, that traditional compensation systems are struggling to deal with (Muralidharan, 2025). Leading global consulting company also back this claim, stating that the full impact of AI on compensation is yet to come, but there are many companies already applying it to attract and motivate employees (Mercer, 2026).

One use case covered in literature is the use of AI to analyse compensation data. Due to the powerful data analysis capabilities that can be unlocked through the use of AI, companies can quickly and efficiently gain insights from vast amounts of internal and external labour market data (Pandey, 2023). AI can analyse multifaceted data quickly, to identify patterns that would be extremely difficult to spot with the human eye alone. Data that relates salaries to other factors such as roles, skills, and geography can be used to more accurately make decisions in relation to compensation. This ultimately leads to compensation packages that are not only more competitive, but also responsive to the labour market.

One of the only other use cases mentioned in the literature that falls within the compensation section of the employee lifecycle is for pay equity and bias detection. Pay equity is when employees are paid equal pay for work of equal value, regardless of characteristics such as race,

gender, religion, etc. In an ideal world this would be the case universally. However, this is not always the case, e.g. the European Parliament estimate that the gender pay gap in the EU sits at 12% (European Parliament, 2025). To solve this issue within companies, agentic AI solutions can be deployed to analyse payroll data and identify these types of discrepancies by monitoring employee salaries and searching for data that indicates bias. The AI models can then make suggestions on how to improve payroll structures to reduce bias and improve fairness (Lakhamraju, 2025).

The importance of addressing pay inequity is clearly demonstrated in a 2025 empirical study surrounding pay transparency and productivity, where over 20,000 employees were tracked. The finding showed that when employees discovered they were being underpaid they were more likely to put in less effort, in comparison to those who discovered they were overpaid who worked harder (Gutierrez et al., 2025). This suggests that overall, it is inequity, not a lack of transparency, that negatively impacts performance and motivation. The study reinforces why AI tools that are capable of detecting pay inequity represent a valuable technological development in compensation.

In both of these examples of uses for AI in compensation there is a great deal of automation. In both cases it saves HR professionals countless hours of analysing both internal and external data. In theory AI allows for enhanced decision-making for all matters related to compensation, as the human decisions are informed by the powerful data analysis conducted by the AI models, allowing for bias free decisions that should enhance the company's ability to not only reward its current employees, but also attract future ones (Alam & College, 2020). However, as previously discussed, the actual quality of these decisions is highly dependent on the quality of the AI itself. If the AI algorithms used in these models are trained on flawed data containing biases or inequalities, it may lead to poor recommendations and even increase inequality in some cases (Bandara et al., 2025). While this is true across all applications of AI in HRM, it is a particularly sensitive ethical concern for compensation, as decisions related to pay greatly impact employees and their wellbeing. For this reason, it is imperative that the AI models are properly trained and monitored if companies truly want to enhance their decision-making.

4.5 Other uses of AI in HRM

Beyond the uses in the four stages of the employee lifecycle covered in the previous sections, it is also important to recognise other applications that lie outside of these parts of the employee lifecycle framework. The literature covers several additional uses of AI in HRM that help professionals to automate processes and make better decisions. One use that is extensively covered in the literature is HR analytics. This is the process of turning employee data into an output that enables companies to make informed, data-driven decisions, and it can now be powered by AI (Ayanponle et al., 2022). Apart from its use in compensation, AI powered HR analytics can be used for a range of other functions such as sentiment analysis to gauge employee satisfaction, and stress levels (Jawaid et al., 2026). The capability that AI provides to quickly analyse large amounts of organisational data not only saves HR professionals time but also enhances their ability to make decisions.

The area of knowledge management has also been largely impacted by AI in recent years. Software company ServiceNow describe HR knowledge management centres as a central hub for HR information within a company, that contains organised resources for employees (ServiceNow, 2026). This frees up time for HR teams to tackle other tasks. These centres are now being further enhanced by AI algorithms and predictive analytics to expand the base, and make retrieval more efficient, as well as giving each user a personalized experience (Gupta, 2025).

Furthermore, these knowledge management centres can be linked to AI powered HR chatbots. Natural language processing and machine learning help to provide employees constant access to a virtual HR assistant that can answer queries and guide employees through HR tasks (Mercy, 2025). This once again shows a high level of automation of a task that would have been done manually before the introduction of AI. Instead of coming directly to the HR professional with a question, employees can simply ask the chatbot, saving time for HR professionals and allowing them to concentrate on decision-making. The literature once again raises ethical concerns surrounding AI chatbots, citing potential misuse of personal data, and biases as issues that need to be tackled with transparency and inclusive algorithms (Suhonen, 2025).

Perhaps the most obvious use of AI in HRM is that of generative AI. Use of generative AI chatbots such as ChatGPT or Microsoft Copilot has grown exponentially in recent years, with people using them to complete tasks in all aspects of life. This is also the case within businesses and within HR departments. Large Wall Street banks have invested billions into generative AI. According to Forbes two of America's largest banks budgeted to spend over \$5 billion on AI last year (Forbes, 2026). Many companies now have their own internal versions of these generative AI chatbots, which HR teams can use to reduce time spent on administrative tasks. These chatbots can be used for a wide variety of functions, driving increases in employee engagement and greatly increasing the operational efficiency of HR teams (Khan et al., 2024).

To conclude the literature review section of this study, the existing body of literature on the use of AI in HRM makes it very clear that AI is profoundly reshaping HR processes across organisations. From conducting AI-powered interviews, to personalising employee learning journeys, assisting with goal setting, and detecting pay inequalities, the different applications examined in this review demonstrate that AI is influencing virtually the entire employee lifecycle. However, two things are also abundantly clear. Firstly, there seems to be an uncomfortable tension between the efficiency gains that can be achieved through AI, and the ethical concerns that also arise from its use, particularly in relation to bias lying within AI algorithms, and the potential decrease in human oversight in important decisions. Secondly, is the scarcity of research covering how AI is actually being deployed in practice, in real organisations and industries, such as banking. This gap provides the justification for the qualitative research that follows, which has been conducted as part of this study, seeking to move beyond theoretical use cases and discover the actual reality of AI in HRM, through the lens of banking HR professionals.

5. METHODOLOGY

Following the review of the existing literature on the different application of AI in HRM, the next part of this study involves a qualitative research design to explore the use of AI in HRM particularly within the banking industry. Looking back on the research questions that this study aimed to answer, all three research questions are of an explorative nature, aiming to gain insights to understand how AI is applied in practice and how much of an influence it has on decision-making. For this reason, qualitative research is the most appropriate for this study, which is more effective for gathering in depth answers to complex questions through profoundly understanding the experiences and perspectives of participants (Saunders et al., 2019).

Within qualitative research, semi structured interviews were chosen to give flexibility in each interview to explore emerging themes in detail (S.Lewis-Beck et al., 2004). The interviews were approached in an inductive manner. As it is an explorative study, rather than testing a predetermined hypothesis, the objective was concerned with generating insights, suitable given the limited research on the practical uses of AI in HRM within the banking industry.

Non-probability, purposive sampling was used to select participants with appropriate experience and sufficient expertise in HR functions, all from within one of the world's largest multinational banks. This sampling method ensured that the selected participants were well-positioned to give relevant insights into the use of AI within their respective domains. While ten participants were initially targeted, the final sample size was comprised of six participants across the areas of L&D, Recruitment & Selection, Compensation, and AI Governance (Full participant details available in Appendix I). The Performance Management perspective was not ultimately captured due to access constraints. It is important to acknowledge that due to this, the study carries certain limitations, as the findings are limited to the HR functions represented. The overall reduction in sample size can be addressed through the principle of data saturation, which is defined as the point at which additional data collection does not yield new themes or insights (Saunders et al., 2019). This concept highlights that it is not necessary in qualitative research to meet a predetermined numerical target of participants once the data gathered is rich and consistent. Across the six interviews there was a clear thematic overlap, with later

interviews consistently corroborating patterns observed in earlier interviews. In practice, this saturation was evident in the later interviews, with a clear convergence observed from the fourth interview onwards. While the dataset is smaller than initially planned, the principle of data saturation suggests that it has sufficient analytical depth for this study.

Primary data was collected from the semi-structured interviews conducted with each HR professional. The interviews were designed to be roughly 45 minutes in length, and all interviews were conducted virtually via videoconference. Interview guides (Available in Appendices II - V) were developed to include core questions to ensure consistent exploration across interviews, whilst also containing open questions that allow flexibility to probe deeper into more particular areas of interest depending on the participant. With the consent of the interviewees, interviews were recorded to ensure accuracy in the transcription process.

The data collected was then analysed using thematic coding analysis through manual coding of interview transcripts, allowing for identification of patterns and themes within the qualitative data gathered from the interviews. Each interview was reviewed in detail, with quotes relating to each research question being extracted, and being assigned a code to represent its meaning in the context of the research question. Similar quotes were then grouped together to establish themes which reflect recurring patterns across the participants (Data analysis tables available in appendices VI – VIII). To augment the reliability of the coding process, intercoder reliability was ensured through a review of the coding framework by the research supervisor, who verified the codes and themes identified in the findings.

To further enhance the credibility of this study, several precautions were taken to ensure this research was conducted in line with ethical standards. All participants were clearly informed about the purpose of the study and the role that they played within it prior to conducting the interviews, and their informed consent was also received. To ensure confidentiality and anonymity for the participants, neither their names nor the name of their organisation were disclosed. Information that could be used to identify them was removed during the transcription process. Additionally, interview data was stored securely and used exclusively for the academic purposes of this study.

6. FINDINGS

The following figure provides an overview of the key findings across all three research questions, which are explored in more depth in the sections that follow:

| <i>RQ1: Current Uses</i> | <i>RQ2: Automation Extent</i> | <i>RQ3: Decision Support</i> |
|--|---|---|
| 1. AI-Powered LXP Learning personalisation | 1. Admin-first approach Low complexity tasks automated first | 1. AI supports, not decides Hybrid human-AI model |
| 2. AI Recruitment Tools Descriptions, feedback, scheduling | 2. Quantifiable Efficiency Gains Measurable time and cost savings | 2. Tangible Insight Gains Influence on learning vendors |
| 3. Universal HR Agent Daily use of internal AI & Copilot | 3. Human-in-the-loop Partial automation as current norm | 3. Bias & EU AI Act Governance limits AI |
| 4. Uneven Adoption L&D advanced, Compensation basic | 4. Automation Paradox AI creating tasks alongside savings | 4. Experience Gap Senior staff spot AI errors |
| 5. AI Literacy as a Priority Top-down AI upskilling drive | | |
| <i>Cross-cutting findings across all three RQs</i> | | |
| Phased deployment Admin to strategic over time | Ethics & Bias Concerns Tension persists across all functions | Governance as Enabler Trust unlocks deeper adoption |

Figure 1: Overview of key findings

6.1 Research Question I Findings

Theme 1: AI-Powered Learning Experience Platforms and Learning Personalisation

The L&D function clearly stands out as an area that has been transformed with the implementation of AI within the bank. This can mainly be attributed to the implementation of the AI-driven Learning Experience Platform (LXP), which houses the entire learning experience from the employee's perspective.

"We onboarded Degreed, which was the Netflix of learning. It's an AI platform that does recommendations, picks up trends, algorithms, and it'll surface content that you are interested in based on your skill set." – Interviewee 5

The LXP gives learners access to a highly individual learning experience, far more personalised than previously feasible. The AI algorithm that powers the platform analyses individual skill profiles and behavioural patterns to recommend content that is tailored to each employee's development needs. Both L&D interviews corroborated this capability, confirming its value within the bank's learning infrastructure.

"When you start learning something or when you start searching something, it understands your patterns and then it starts getting your recommendations. It is exactly like how your social media works." – Interviewee 1

The participants powerfully attested that the implementation of AI in L&D has produced a change in how the employees relate to learning. Previously learning was seen exclusively as something that had to be completed for compliance reasons. In stark contrast, interviewees spoke of a cultural shift, where a more dynamic learning experience aligned with what employees actually want to learn.

"So that's kind of a big transformation piece where organisations have been going from that standard LMS, which is, you've got to do that learning, and you've got to do it by this day, or you get told off by your manager, versus, hey, take a look at this and develop and grow." – Interviewee 5

Aside from improving the learning experience for the employees within the bank, AI also enhances the operational side of L&D at the bank. AI assists with maintaining the quality of the learning platform. One participant spoke of an ongoing project where they are using AI to organise learning content through taxonomy and categorisation, allowing for more efficient reporting and compliance tracking.

"We need to be able to look at all this learning and create a sort of taxonomy and align each piece of content to categorisation that we've designed in the bank. And this will be done using AI." – Interviewee 5

Theme 2: AI Being Applied Across the Recruitment and Talent Acquisition Lifecycle

Another area with a particularly strong use of AI is within recruitment and selection. The interviews clearly demonstrated that AI is now embedded across multiple stages of the recruitment process, starting with job design, and reaching as far as post interview feedback. Internal AI agents are assisting with tasks such as writing job descriptions, drafting interview questions for managers, and writing post interview feedback for applicants. AI is also being used in a broader talent development context, helping to automate matching of profiles accurately within the bank's mentorship programme.

"We have all agents in the internal AI, for example to do the job description for the role. It helps us to prepare the job description for the role, question for the interviews, feedback for candidates." – Interviewee 3

Furthermore, AI is also reshaping the values and standards that actually define the recruitment practice itself. One interesting point raised in relation to interviews was the fact that candidates are expected to demonstrate AI literacy within interviews, as it is a mandatory requirement to include questions on AI in all job interviews within the bank. This is due to the fact that employees are expected to be comfortable working with AI tools from day one, reflecting how AI is redefining the profile that is sought in the talent acquisition process. Despite this, AI currently seems to be confined to the more creative tasks noted above, for example it has no role in candidate screening. One participant mentioned a previous AI system used in candidate screening, however, it has since been discontinued and replaced with a rule-based system due to reliability concerns.

"The previous system we had was doing a matching score automatically — the system will match candidate, like one star to five stars, depending on how the person is matching the role." – Interviewee 3

Theme 3: AI as a Productivity Tool in Daily HR Work Irrespective of Function

Outside of any particular HR functions, there were clear trends that arose in all interviews which help to understand the more general uses of AI in HRM. The bank's in-house AI

platform, as well as Microsoft Copilot, are seen as universal tools that are used on a daily basis by HR employees. It is often used to help with very simple tasks such as drafting emails and summarising meetings. Another noted use case was for formula troubleshooting for calculations in Excel. The internal AI is clearly seen as the preferred tool that is governed and sanctioned by the bank, with Copilot further enhancing the GenAI deployment within the bank.

"We use it all the time, the internal AI, for everything, pretty much." – Interviewee 5

Beyond simple individual use for productivity, it was also apparent from the interviews that AI is integrated into operational workflows across all HR functions in the bank. The clearest example of this is the universal HR chatbot agent that has been created within the bank, which houses all HR functions in one interface. It allows employees to access information and solutions easily across the full employee lifecycle, e.g. simple questions about payroll or annual leave. This saves time for both employees and HR professionals.

"We have the HR agent, which kind of houses everything — it has compensation, it has recruitment, it also has people solutions centre, L&D of course is a part of it. So, all the functions that run in the HR team are managed by this agent." – Interviewee 1

Theme 4: Barriers, Constraints, and Unevenness in AI Adoption Across HR Functions

While AI adoption is clearly progressing across various HR functions, the pace at which the adoption is taking place is dependent on multiple factors. Human and cultural factors certainly account for this. One interviewee observed a generational disparity in AI adoption. Younger people who tend to be more digitally native, have adapted easier to the arrival of AI to HR, while older staff tend to continue working in their usual habits. It was also noted that it is attitude dependent, as there needs to be a willingness and ability to change to work more efficiently.

"New generation people, they are quite easy to adapt. But the people who have been in the system for a lot of time, when you work, you get into your way of working, and you just keep on following the steps." – Interviewee 3

Pace of adoption also seems to depend highly on the function within HR. While L&D has seen a significant transformation, other areas such as compensation operate at a far less advanced level in terms of AI integration. Within compensation, interviewees described AI use as being primarily confined to administrative tasks such as those covered in theme 3. The function is still in the early stages of uncovering how to embed AI into its core processes and workflows. Adoption is very dependent on the particularities and varying nature of each function's work, with factors such as data sensitivity or regulatory compliance creating a more difficult environment for AI integration in some areas.

"AI in compensation, I think relatively, it's very new and still in a baseline kind of thing. And just the beginning of AI being introduced in compensation." – Interviewee 2

Despite the current limitations, there was a confidence amongst all participants that AI adoption will deepen with the passing of time, with some outlining trust in governance and wider market conditions as factors that will heavily influence future enablement. In compensation again, for example, both interviewees expressed that wider adoption within the function is dependent on the bank becoming more comfortable with the frameworks that govern data usage, and also the accuracy of the AI systems themselves.

"That adoption will likely increase gradually as organisations become more comfortable with the governance and accuracy." – Interviewee 4

Theme 5: AI Literacy, Upskilling, and AI as a Subject of Learning Across the Bank

One highly interesting insight uncovered during the interviews is that AI adoption is not just something that the HR team within the bank does themselves, but it is also actually a subject that they teach. For the L&D function within the bank, AI clearly stands out as the single most in demand learning category across the workforce, with AI learning attracting thousands of completions. Individuals noted that they are already reaping the benefits of this training, with multiple participants mentioning a particular prompt engineering learning that has improved their ability to generate quality AI outputs.

"They've got tens of thousands of hits on those AI course completions, whereas some of the courses out there have only got two or three people doing them." – Interviewee 5

This is not something that has happened by accident, but rather an institutional priority that is being driven at an executive level. Multiple interviewees described this as a structured push that is helping to embed AI across teams and is supported by formal training initiatives designed to facilitate the use of AI, particularly within HR. Despite this movement, AI adoption is still in its infancy, however the bank, and indeed the HR teams, are strategically positioned to further rollout AI initiatives.

"There is a huge push on AI in the bank from the top down." – Interviewee 5

6.2 Research Question II Findings

Theme 1: Automation of Administrative and Repetitive Tasks as the Current AI Use in HR

Across all HR functions covered in this study, a clear consistent pattern emerged, where AI is actively used to automate low-complexity, high repetition manual tasks. Interviewees across functions described this as a deliberate approach that has been taken with the view that simple administrative tasks are an appropriate starting point for deploying AI, and that more complex applications are to follow as people grow more confident and become comfortable with AI itself.

"I think there's a huge amount that can be automated. And I would definitely start from the more mundane aspects, like the information extraction, scheduling meetings, stuff like that."

– Interviewee 6

This phased implementation model is evident across all HR functions which were interviewed, and many concrete examples were uncovered. AI has helped to automate annual course relevancy attestations and assigning mandatory compliance learning in the L&D function, something that was previously done manually for every single employee that joined the bank. In compensation AI has automated basic payroll calculations, and other tasks such as extracting

headcounts and reporting data. In recruitment, AI can automate repetitive tasks such as extracting basic structured data from CVs.

"Anybody who comes to the bank needs to do certain learnings, which earlier the HR team was sitting and assigning. And now AI does that for us." – Interviewee 1

Considering the above examples, the data extraction and reporting use stands out as the most advanced and consistent area of automation across HR within the bank. Prior to the use of AI in this field, generating reports was a task that required days of manual downloading and extracting, involving multiple people, and creating significant delays for stakeholders. Automation through AI has been able to compress these processes significantly.

"Managers do not have to wait around for three or four days now. It is just a matter of a few hours, and they get the report to them." – Interviewee 1

Theme 2: Quantifiable Efficiency Gains and Capacity Reallocation from AI Automation

Some of the most striking insights gathered in this study relate to the efficiency gains achieved through automation, with interviewees providing concrete, quantifiable evidence of time and cost reduction. The standout example of this is with content creation in L&D. Previously this was a process that would typically last up to 20 weeks, from scoping and subject expert collaboration to script writing and storyboarding. Through AI this entire process now lasts just a matter of hours. These savings can also be quantified in cost. Previously the bank paid translation companies to translate content into Portuguese for the Brazilian audience, something that is now also done through AI.

"What would have taken us typically a 20-week process — AI can reduce that down to probably a couple of hours of work to just pull that content together." – Interviewee 5

The time savings achieved through automation means that HR professionals within the bank not only complete their work faster but are able to use the time savings to concentrate on higher-value analytical and strategic tasks. In L&D in particular, it was highlighted that AI has allowed

for a shift in the team's focus, from data extraction to data interpretation. This highlights how AI automation is not just an efficiency tool, but actually an enabler of role evolution.

"It's just to support that and buying time back for us to have a more strategic focus on what our other responsibilities are." – Interviewee 4

Furthermore, many of the participants expressed the belief that there is a substantial automation potential that remains unrealised. In compensation for example, one of the participants presented a vision of an on-demand headcount reporting tool, which they described as a near-term aspiration. The automation potential is highest where task repetition is greatest.

"If they type, 'I need a headcount and a comp data as on this date,' it should directly give. And then they can start their analysis." - Interviewee 2

Theme 3: The Human-in-the-Loop: Persistent Human Involvement as a Principled Boundary on Automation

Despite all of the gains and efficiencies achieved through AI automation in HR, the interviewees were keen to highlight that human involvement was purposefully retained, stressing the importance of the “human-in-the-loop” process across multiple functions. This concept refers to the need for humans to be involved at some point in the AI workflow, ensuring accuracy and accountability. This is an essential consideration in the bank when using AI to automate processes, and any AI output is thoroughly checked, even when it seems to be valid at a surface level.

"Even if things are running smoothly, I still think you need to have that go in, validate it." – Interviewee 5

This hybrid model of AI generation and human verification is further emphasised through various examples raised in the interviews and can be referred to as partial automation. In L&D for example, with AI content generation, the AI produces the first draft, which the human can then adapt to ensure it is appropriate in the context of the bank. In recruitment, AI can handle

scheduling and administrative communication with candidates, while the human maintains direct contact at key points. This model is not just a transitional state, but a deliberate operating model.

"The internal AI does give us content, but then we have to sit and define it, design it and everything." – Interviewee 1

While the more established model at the current moment is partial automation, there are a small number of tasks that have exceeded this and reached full automation, with more tasks also approaching this stage. The most concrete example of this is the aforementioned conversational AI HR chatbots, which achieve fully autonomous HR querying for employees within the bank. With a thought to the future, it was made clear that many other HR tasks will soon also become fully automated, with one interviewee describing the onboarding process as something that is likely to be fully automated in the near future.

"If I go to that agent and just ask how much leave do I have left, it kind of just gives me everything. I do not have to go to a record like here and there." – Interviewee 1

Theme 4: The Automation Paradox: AI Creating New Burdens Alongside Reducing Old Ones

Perhaps in contrast to all the positives of AI automation in HR uncovered in this study lies the automation paradox. The counterintuitive finding, which was raised most prominently in the recruitment interview, raises the fact that while AI reduced the time spent on some tasks, its use has created additional tasks that did not exist before. Examples of this are mandatory learning to gain access to the internal AI platform, and the need to ask questions about AI literacy in interviews. While AI does save time, it also creates new demands, complicating the straightforward narrative that typically goes along with AI adoption.

"It's mandatory to use those tools at the bank. Like it's part of the process now. You have to use the internal AI. You have to do those trainings also beforehand on AI. So indeed, it's adding more tasks on the plate sometimes." – Interviewee 3

Beyond concerns about workload, some participants also expressed apprehension about the long-term human consequences of AI automation. There was an argument presented that as AI generates more of the responses, the underlying competencies of the HR professionals begin to fade. The paradox deepens with the consideration that organisations must invest in AI upskilling whilst AI also simultaneously erodes the foundational skills of the practice.

"It's removing some learning path for the people. Like I think then we are becoming a bit lazy and not doing things." – Interviewee 3

Perhaps the most alarming negative raised in relation to AI automation was the distinct possibility of AI removing positions within HR, leading to job losses. This was seen within recruitment once again, as the participant outlined processes that would be entirely automated, such as CV screening, which as a direct consequence would mean that fewer recruiters are required within the bank. This prediction carries a particular weight, as it is not an external forecast, but an insider's assessment of the future of their own role.

"We will need less recruiters, because we will remove some tasks such as screening interviews. We may be involved maybe at offer stage, I believe, because that's sometimes a tricky discussion." – Interviewee 3

6.3 Research Question III Findings

Theme 1: AI as a Decision-Support Tool, not a Decision-Maker

In the context of decision-making one thing that was made abundantly clear across all interviews is that while AI supports decision-making, it does not make decisions itself. In L&D, it is stated that AI aids with reflection and gathering information needed to inform choices but does not direct the outcome itself. Similar examples were also covered in other functions, suggesting that this is not accidental, and rather that it reflects a widely shared professional norm across HR within the bank.

"I think AI for me; it helps me take better decisions. It does not decide for me. AI is not yet equipped like that." – Interviewee 1

A clear hybrid model has emerged, where AI provides data driven input, which humans then interpret to provide a final judgement. AI was acknowledged to be able to provide a level of objectivity that humans cannot in relation to recruitment bias. However, this only applies to a certain extent, with cultural fit assessment being outlined as something that is currently beyond the capabilities of AI.

"At some point we say that AI can be more objective. But we always have to make sure that we are fair with the process with the candidates. And I think that's why we need both." –

Interviewee 3

Furthermore, purely from a governance perspective there are certain tasks where human oversight is more than just a recommendation, but a requirement. Looking into hiring decisions for example, the sensitivity of the decisions means that an expert in the field must always be present in the decision-making process. Participants framed oversight as a way to manage risk, and an obligation rather than a choice. Even as AI becomes more advanced in the future, human involvement should remain as a permanent design principle, as it is not just a feature of technology that has not fully matured yet.

"I don't think it should ever really get to the point where it's an entire AI system deciding whether someone gets hired for a particular role. You need always to have experts in that process." – *Interviewee 6*

Theme 2: Where AI Does Enhance Decisions: Concrete Evidence of Insight-Driven Improvement

There were multiple examples of just how powerful AI is as a decision support tool within the bank, with some interviewees presenting tangible gains achieved through AI assisted decision-making. The most striking of these comes from within L&D, where platform engagement analytics powered by AI is actually shaping investment decisions. With the AI learning reporting tool, HR professionals can easily stay on top of new learning trends such as microlearning, or content on AI, and cater their vendor choice accordingly. It was also pointed

out AI can be used to support people business partners and help them make the right decisions when managing difficult employee relations situations.

"Activities like what is attracting a lot of people — if people are utilising a lot of TED Talks or spending a lot of time on LinkedIn Learning. So accordingly, we can cater our vendor services." – Interviewee 1

Interviewees were also keen to describe exactly how AI helps to improve their decision-making. One example is that instead of delivering single recommendations, AI has the creative capacity to quickly generate multiple options of decisions that can be made in a given situation, then allowing the HR professionals to evaluate the alternatives and make the most informed choice. It can also help make decisions in moments of uncertainty, when deciding between two options for example. AI has the ability to objectively look at both options and provide data insights to help surface the most appropriate path. AI consistently introduces new perspectives that the human might not have thought of previously, making it a powerful tool in the context of decision-making.

"If I'm confused, if I should do this or that, and then you give everything to the AI — it analyses a lot of data for you and that gives you what is correct." – Interviewee 1

Another dimension of AI decision-making within HR is its reach and impact on the rest of the organisation. In L&D, the AI generated reports on learning analytics are passed to senior business leaders, making people related data more visible within the organisation. This example enables managers to make informed decisions about their team's development. It is apparent that the benefits of AI-driven decisions are not only beneficial for the HR team, but for the bank as a whole.

"Also sharing the reports to other business leads so that they know what each team is doing, how much of learning their team members are doing." – Interviewee 1

Theme 3: AI Bias, Algorithmic Opacity, and Regulatory Constraints: The EU AI Act and the Limits of AI in HR Decisions

The interview with the AI governance expert gave a unique introspect regarding exactly how and why AI being involved in decision-making is an extremely sensitive topic. Governmental bodies are having to rapidly come up with legislation to control the use of AI in organisations, a task that is challenging due to the continuously evolving capacity of AI. The best example of this is the EU AI Act, which is the primary regulatory framework covering the use of AI decision-making, with the participant particularly pointing out the provisions around using AI for hiring and firing decisions. These regulations fundamentally limit how much AI can be implemented into decision-making processes. The bank also recognises the importance of AI regulation, as there are internal institutional governance frameworks which were also referenced in the interviews.

"The few AI regulations that exist are in these kinds of scenarios where you're using AI to make decisions about people, like the EU AI Act. That's specific kind of policies in there about using it to make decisions about hiring people or firing people." – Interviewee 6

Beyond regulation, the same interviewee also provided an insight into the technical risks that make AI decision-making more difficult to implement. The shift in recent years to pre-trained large language models (LLMs) such as ChatGPT, which are essentially trained on every piece of text available on the internet, means that it is difficult for organisations to have a direct insight into how the models arrive at any given output. This opaque nature means that despite the models being perfectly able to give accurate responses on most occasions, it is very difficult to spot when a model gives an output that is not fully correct.

"You don't have any real insight into what information the model has access to. And the models are so complex, it's very difficult to try and look at the internals and see how they came to different decisions." - Interviewee 6

The potential margin of error mentioned above has the potential to be devastating for organisations if it is not managed correctly. The interviewee highlighted this through an anecdote about Amazon's early attempts to implement AI into HR decision-making. The model deployed was trained on historical data and replicated the gender discrimination at scale due to

the fact that there were very few female profiles in the dataset, despite not being instructed to perform in this way. The consequences of this are a double-edged sword, as not only do good candidates slip through the cracks, but the company can also be held liable in the court of law for these types of situations. Inappropriate AI deployment in HR decision-making can produce serious harm at a sector-wide level, which is why it must be done so cautiously.

"They deployed a hiring algorithm to screen initial applicants and trained it on historical data. And then they realised that the new algorithm was essentially only suggesting men." –

Interviewee 6

This danger is further highlighted by the seemingly contrasting opinions across interviews, with some participants being very risk-orientated when discussing AI implementation in decision-making, and others having a more relaxed approach. One interviewee dismissed concerns about AI data risk, stating that they thought it stems from a lack of education rather than a genuine threat. There is a clear tension between this type of thinking and that of the governance expert.

"I think that concern comes from a lack of education on it as opposed to there being a true level of risk being there." – Interviewee 4

Theme 4: Human Experience, Knowledge, and the Conditions for Valid AI-Assisted Decision-Making

One interesting point that was made in relation to decision-making with AI was that AI driven insights can only offer as much value as the person that is interpreting them. One participant raised the point that more experienced professionals are able to look at AI generated insights and easily identify when something doesn't look right, something that is not as easy for less experienced HR professionals. There is an apparent risk created by this dynamic, as less experienced staff are exposed to the jeopardy of having a false confidence in outputs, the same people whose underlying skills were previously labelled as eroding due to the use of AI. This risk is further compounded as the more experienced staff exit the workforce, leaving organisations even more reliant upon AI.

“The person who has worked for 7, 8 years in compensation would definitely look at the numbers and know that something is wrong. And if similar data is given to someone who is new, they won't understand that much.” – Interviewee 2

It is evident that AI's current decision-making role in HR remains limited and heavily reliant upon human judgement, however the interviewees did seem confident that this balance will shift over time. In compensation, one interviewee anticipated that AI tools could eventually replace third-party platforms as the primary source of market benchmarking data. Salary decisions themselves were also identified as a potential future domain for increased AI influence, though contingent on governance maturity.

“Maybe if we are using more into AI, maybe in future, we won't have a system like Payfactors. But internally, we can create all such tools. So that will happen eventually.” – Interviewee 2

7. DISCUSSION

The findings of this study offer a detailed insight into the adoption of AI in HRM within the banking industry, both corroborating and challenging the existing body of literature. An empirically grounded view is given on how AI is actually being used within the HR function of a large bank, as opposed to how the literature suggests it is.

In recruitment and selection, the findings align with the literature's assertion that the function represents a leading use case for AI within HRM, but in a slightly different manner than what the literature implies. The use of AI for tasks such as job description, interview question generation, and candidate feedback confirms that AI is meaningfully embedded in the recruitment process, however the AI CV screening that was highly documented in the literature is not something currently employed within the bank. There is a clear gap between what the literature presents as standard practice, and the more cautious reality.

In L&D, the findings are very strongly corroborated, particularly surrounding the implementation of the Degreed LXP in the bank, which is lauded in the literature for its capacity to offer personalised learning pathways to employees. The cultural shift from learning purely for compliance to learning to develop echoed by both L&D interviewees also reflects how the literature highlights that AI-powered personalisation improves employee retention and engagement. The quantifiable efficiency gains uncovered in the study extend beyond what the existing literature is able to offer, representing an original empirical contribution.

The compensation function is where the findings most sharply contradict the literature, as multiple authors framed AI in compensation as already being significantly deployed and having a huge potential in reducing pay disparity and salary benchmarking. The interviewees presented a more cautious approach, with AI use in compensation being confined to administrative tasks. The literature very much overstated the maturity of AI adoption, proving the value of qualitative primary research that is able to provide an organisational reality.

The most counterintuitive finding uncovered in the study is that of the automation paradox. This is the reality that while AI adoption reduces certain tasks, it also creates new ones. This dynamic is absent from the existing literature, which focused purely on efficiency gains. This study therefore suggests that a complete account of AI's impact on HRM must consider additional new tasks such as mandatory AI training, and the introduction of AI literacy questions into job interviews.

A significant tension emerged between the perspectives of the AI governance expert and one of the compensation employees. The governance expert was keen to highlight concerns about algorithmic bias, LLM opacity and legal frameworks such as the EU AI Act, many of which were also heavily expressed in the literature. On the other hand, the compensation interviewee dismissed these concerns, stating that they come from a lack of education. This divergence between two professionals from the same organisation is striking and suggests that governance awareness within HR functions is not as uniformly appreciated by HR professionals, as the literature suggests.

It is also important to note once again that while this study has helped to uncover some highly interesting discussion points, it is not without limitations. The absence of the performance management perspective, which could not be captured due to access constraints, leaves a gap in the coverage of the HR lifecycle. It also must be noted that this study was based on a single banking organisation, limiting how much the findings can be generalised across the broader banking industry. A future study covering multiple banks, whilst also incorporating the performance management aspect would significantly strengthen the evidence in this area.

8. IMPLICATIONS FOR PRACTICE

The findings of this study carry several practical implications for HR professionals and banks, as well as more broadly for any organisation currently navigating the challenging landscape of integrating AI into their HR function. Firstly, a phased approach to AI implementation is recommendable. The findings clearly highlight that the most successful AI deployments within the bank are those that target low-complexity, high repetition administrative tasks. Organisations must apply a deliberately phased approach, starting with administrative automation, where successful implementation can lay the foundation for application in more complex areas down the line. This minimises risk for the organisation but also allows HR teams to build the AI literacy and trust required to execute more complex uses of AI.

One of the clearest findings of the study is the need to invest in AI literacy in order to be able to harness and extract value from AI tools. Many interviewees who had completed AI trainings in areas such as prompt engineering expressed that it has helped them achieve better outputs from AI tools. This has direct implications for HR departments, as AI literacy is now becoming not an optional extra, but actually a strategic priority. The bank's top-down drive for AI upskilling is admirable in the current day and is a model that would be beneficial for many organisations.

Across all areas examined in this study, human involvement was purposefully retained. The interviewees consistently framed this as a governance requirement that exists within the bank's AI governance framework. Organisations must create governance frameworks that define how AI can be used and where human authority must be retained. Failing to do so risks not only harming decision quality but also facing legal liability due to the existence of regulatory frameworks such as the EU AI Act.

One of the most concerning findings from the study was the lack of consistency in governance awareness between the AI governance expert and the compensation interviewee who dismissed its importance. This divergence clearly highlights that organisations need to ensure that AI governance awareness is not something that applies to specific AI teams, but to the entire HR

teams and furthermore the entire organisation. This can be achieved through initiatives such as mandatory AI governance training for all employees, and education on frameworks that outline what data can be given to AI systems.

While AI does help automate repetitive tasks, allowing HR professionals to dedicate time to more strategic tasks, the counterintuitive automation paradox also reminds us that while AI does eliminate certain tasks or make them more efficient, it also generates new obligations for employees. It is important that organisations proceeding with AI rollout within HR factor these extra tasks into workload planning, and that leaders do not assume that automation directly translates into enhanced capacity. It is imperative that HR professionals are not burdened with even more work than they previously had, as this undermines the case for AI adoption and would damage the wellbeing of HR teams that are expected to use it.

AI is not just a trend. It is a reality that is here to stay, and its influence on HR will only continue to grow. Organisations who do not adapt risk falling behind, as the question moves further away from whether to adopt AI into HR processes or not, and towards how to implement AI into HRM responsibly. The bank covered as part of this study lays out a clear blueprint on how to deploy AI within HR. Organisations that are able to replicate these foundations, both within banking and other industries, will be strongly positioned to benefit from AI as it continues to develop in the coming months and years. Those who do not achieve this risk falling behind and exposing themselves to the ethical and legal consequences that can arise from implementing AI without the proper guardrails in place.

9. CHAT GPT USAGE STATEMENT

Declaración de Uso de Herramientas de Inteligencia Artificial Generativa en Trabajos Fin de Grado

ADVERTENCIA: Desde la Universidad consideramos que ChatGPT u otras herramientas similares son herramientas muy útiles en la vida académica, aunque su uso queda siempre bajo la responsabilidad del alumno, puesto que las respuestas que proporciona pueden no ser veraces. En este sentido, NO está permitido su uso en la elaboración del Trabajo fin de Grado para generar código porque estas herramientas no son fiables en esa tarea. Aunque el código funcione, no hay garantías de que metodológicamente sea correcto, y es altamente probable que no lo sea.

Por la presente, yo, Jamie Christopher Ivory, estudiante del Grado en Administración y Dirección de Empresas con Mención en Internacional (E-4) de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado "Exploring the Use of Artificial Intelligence in Human Resource Management Across the Employee Lifecycle: A Qualitative Study of the Banking Industry", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. **Brainstorming de ideas de investigación:** Utilizado para idear y esbozar posibles áreas de investigación.
2. **Corrector de estilo literario y de lenguaje:** Para mejorar la calidad lingüística y estilística del texto.
3. **Sintetizador y divulgador de libros complicados:** Para resumir y comprender literatura compleja.
4. **Revisor:** Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.
5. **Generador de encuestas:** Para diseñar cuestionarios preliminares.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 03/06/2026

Firma: _____



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11. APPENDICES

APPENDIX I: Participant Details

| | <i>HR Function</i> | <i>Role Level</i> | <i>Gender</i> | <i>Interview Length</i> |
|----|------------------------|-----------------------|---------------|-------------------------|
| 1. | Learning & Development | Vice President | Female | 45 minutes |
| 2. | Compensation | Senior Specialist | Female | 35 minutes |
| 3. | Recruitment | Senior Specialist | Female | 35 minutes |
| 4. | Compensation | Specialist | Male | 35 minutes |
| 5. | Learning & Development | Senior Vice President | Female | 40 minutes |
| 6. | AI Governance | Vice President | Male | 40 minutes |

APPENDIX II: AI Learning & Development Interview Guide

- Could you briefly describe your role within learning and development?
- Have you noticed any changes in learning and development in recent years?
- What AI tools or systems are currently employed in learning and development in the bank?
- Is the learning platform used within the organisation heavily driven by AI?
- Would you say AI is mainly used to support administrative tasks, or does it play a bigger strategic role in learning and development within the bank?
- Learning personalization through AI features heavily in learning and development literature. How effective is it in practice?
- Have you noticed an increase in demand for training on AI itself?
- Do you use generative AI tools such as ChatGPT, Copilot or internal AI systems in your day-to-day work?
- To what extent has AI automated tasks or made them easier or quicker?
- In what areas of learning and development is human judgment still essential?
- Are there any situations in your role where you would not trust AI to assist with decision-making?
- Is there a risk of learning and development professionals becoming over reliant AI?
- How much do you think AI improves the overall learning experience within the bank?
- How do you think AI will change learning and development over the next few years?
- Is there anything about AI in Learning & Development that we haven't discussed that you think is important?

APPENDIX III: AI in Compensation Interview Guide

- Could you briefly describe your role within compensation?
- How has compensation changed in recent years?
- What AI tools or systems are currently being used within compensation in the bank?
- Is AI mainly used to support administrative tasks, or does it have a more strategic role in compensation?
- One major theme in the literature was the use of AI for pay equity and compensation analysis. Is this something that is done within the bank?
- To what extent do AI-driven insights influence compensation decisions?
- Has AI improved the quality or accuracy of compensation-related decision-making?
- Are there situations where you would not trust AI outputs in compensation decisions?
- To what extent has AI automated compensation process?
- Which areas of compensation still require strong human involvement?
- Is there a risk of organisations becoming overly reliant on AI in compensation decision-making?
- Do you use generative AI tools such as ChatGPT, Copilot or internal AI systems in the compensation function?
- Are there concerns around confidentiality or data privacy with the use of generative AI tools?
- The literature often raises concerns about bias in AI systems. Is this something discussed within your organisation?
- Do you think AI can improve fairness in compensation decisions, or could it unintentionally reinforce inequalities?
- How do you see AI changing compensation over the next few years?
- Is there anything about AI in compensation and that we haven't discussed but you think is important?

APPENDIX IV: AI in Recruitment & Selection Interview Guide

- Could you briefly describe your role within recruitment and selection?
- How has recruitment changed in recent years?
- What AI tools or systems are currently being used in recruitment and selection?
- Would you say AI is mainly used for administrative tasks or does it have a more strategic role within recruit and selection?
- To what extent have recruitment and selection processes been automated in the bank through the use of AI?
- Which recruitment tasks still require strong human involvement?
- How much do you rely on AI-driven insights when making hiring decisions?
- Has AI improved the quality or speed of recruitment decision-making?
- Are there situations where you would not trust AI recommendations in recruitment?
- Are generative AI tools such as ChatGPT, Copilot, or internal AI systems used within recruitment at the bank?
- Are there any concerns around candidate data confidentiality of candidate data with the use of these tools?
- The literature raises concerns around bias in AI-driven recruitment systems. Is this something you have considered?
- Can AI improve fairness in recruitment, or could it unintentionally reinforce bias?
- Do you think AI-driven recruitment can sometimes make the hiring process feel less personal?
- What are the biggest limitations of AI systems within recruitment?
- How important is human oversight when using AI systems in recruitment?
- Is there a risk of becoming over-reliant on AI insights in recruitment?
- How do you see AI changing recruitment and selection over the next few years?
- Is there anything about AI in recruitment and selection that we haven't discussed but you think is important?

APPENDIX V: AI Governance Interview Guide

- Could you briefly describe your role within the AI Governance team?
- What are your main responsibilities on a day-to-day basis?
- From your perspective what are the most common ways AI is currently being used in large organisations?
- How do you see AI being used specifically in HR functions?
- Would you say organisations are currently using AI more for efficiency gains or for strategic decision-making enhancement?
- Why are governance and fairness so important when implementing AI systems?
- The literature highlights concern around bias in AI systems trained on historical data. How significant is this issue in practice?
- How exactly are AI systems governed or monitored within the bank?
- From your perspective where should human judgment always remain central when using AI systems?
- Do you think there is a risk of organisations becoming overly reliant on AI-driven recommendations?
- What are the biggest limitations of current AI systems being applied in HR?
- Do you think people can be too trusting of AI outputs?
- What are the biggest governance or ethical concerns surrounding generative AI specifically?
- Do you think generative AI will fundamentally change HR decision making in the future?
- In your opinion, how will AI continue to influence HR functions in the future?
- Do you think AI will primarily augment HR professionals or eventually replace significant aspects of HR work?
- Is there anything about AI governance or ethics that we haven't discussed but you think is important?

APPENDIX VI: Research Question I Thematic Coding Analysis

| RQ1: What are the current concrete uses of AI across the different stages of the HR lifecycle in the banking industry? | | |
|---|--|--|
| Code | Sub-theme | Theme |
| AI-powered LXP using skill-based algorithms for personalised content recommendations | LXP as AI-Driven Infrastructure | Theme 1: AI-Powered Learning Experience Platforms and Learning Personalisation |
| AI algorithms as the foundational architecture of modern LXP platforms | | |
| Shift from compliance-focused LMS to talent-aligned LXP enabled by AI | | |
| AI-enabled LXP integrating L&D into the broader talent lifecycle | | |
| AI-powered LXP as the foundation of the transformed L&D function | | |
| AI as foundational infrastructure for a culture of continuous learning | | |
| Participant notes AI has substantially transformed the L&D experience | | |
| Skill-profile-driven AI surfacing learning content to individual employees | AI Learning Personalisation | |
| Personalised learning preferences as the primary AI input in learning platforms | | |
| AI personalisation creating individualised learning experiences at scale | | |
| Personalised learning recommendations from AI | | |
| AI enabling needs-based rather than catalogue-based learning content discovery | | |
| AI replacing linear course design with behaviour-responsive learning experiences | | |
| Adaptive learning as AI application at the content delivery stage | | |
| AI fundamentally changing the learning consumption model from compliance to engagement | AI-Driven Change in Learning Culture | |
| Technology investment with AI capabilities producing measurable cultural L&D shift | | |
| AI enabling more efficient learning design and more responsive learning delivery | | |
| AI enabling creative and interactive L&D content delivery and design | | |
| AI enabling micro-learning content formats aligned with decreasing employee attention spans | | |
| AI curated content development vendors entering the market | AI in Content Governance, Strategy, and Organisation | |
| AI-oriented vendor selection as a current L&D procurement strategy | | |
| AI applied to content governance and organisation at scale | | |
| Content taxonomy as an AI-assisted reporting and compliance enabler | | |
| AI-powered self-assessment learning tools | | |
| AI tool development for job description creation | AI as a Content Creation and Administrative Tool | Theme 2: AI Being Applied Across the Recruitment and Talent Acquisition Lifecycle |
| Internal AI agent generating structured interview questions | | |
| Internal AI agent ecosystem covering end-to-end recruitment content creation | | |
| AI deployed to assist with job design, interview, and feedback stages simultaneously | | |
| AI supporting post-interview administrative output | | |
| GenAI embedded in routine recruitment workflow | | |
| AI used for workflow coordination and task management in recruitment | | |
| AI enabling scalable mentorship programme administration previously bottlenecked by manual matching | | |
| AI used within talent development and knowledge-sharing programmes in banking HR | | |
| Recruitment identified as a function with significant remaining AI growth potential | | |
| AI adoption in recruitment framed as ongoing rather than complete | | |
| AI-powered self-assessment learning tools | | |
| AI literacy embedded as a formal recruitment selection criterion | AI Reshaping What Recruitment Values | |
| AI shaping what skills are valued and assessed in hiring | | |
| Rule-based candidate filtering as current AI ceiling in CV review | | |
| Human CV review persisting despite available AI support | | |
| Automated scoring system as an early form of AI-assisted candidate ranking | | |
| Data-driven candidate matching as a prior AI capability | | |
| Candidate personal data systematically fed into AI systems during recruitment | | |
| Internal AI used daily for email response, query handling, meeting summarisation, and information consolidation | GenAI as a Universal Daily Productivity Tool | Theme 3: AI as a Productivity Tool in Daily HR Work Irrespective of Function |
| Internal AI as the primary productivity tool for compensation team communications and knowledge management | | |
| Bank-wide internal AI platform as the infrastructure enabling universal AI adoption | | |
| AI deployed as an assistive productivity layer across all employee functions | | |
| AI tools embedded in existing productivity workflows | | |
| Bank-sanctioned AI as the preferred/governed option | | |
| Both internal GenAI platform and externally developed solutions used in tandem | | |
| GenAI superseding traditional search for technical problem-solving | | |
| Continuous AI development improving experience and capabilities | | |
| Email integration extending AI's reach deeper into team's daily workflows | | |

| | | |
|---|---|--|
| AI as a real-time formula troubleshooting tool | | |
| Unified HR AI agent integrating compensation, recruitment, L&D, and people solutions into a single interface | AI Integration Across HR Systems and Workflows | |
| HR agent as organisational evidence of AI embedding across multiple HR lifecycle stages simultaneously | | |
| GenAI used for routine L&D content writing tasks such as course descriptions and journeys | | |
| Internal AI agent automating report extraction and distribution in L&D | | |
| AI-driven learner engagement strategy replacing traditional communications approaches | | |
| AI replacing manual, labour-intensive documentation tasks | | |
| AI removing compensation team dependency on manual data movement across different HR systems | | |
| Manual inter-system data transfer replaced by automated AI | | |
| AI providing decision support to people business partners managing difficult employee relations situations | | |
| Habitual working practices as a barrier to AI adoption | Human and Cultural Barriers | Theme 4: Barriers, Constraints, and Unevenness in AI Adoption Across HR Functions |
| Workforce experience profile shapes AI integration pace | Uneven AI Adoption Across HR Functions | |
| Limited current AI use cases in compensation | | |
| AI integration in compensation at an early, incremental adoption stage | | |
| AI adoption in compensation as emergent | | |
| Human CV review persisting despite available AI support | | |
| Rule-based candidate filtering as current AI ceiling in CV review | Governance Trust and Market Evolution as Enablers | |
| Both internal GenAI platform and externally developed solutions used in tandem | | |
| Governance confidence and accuracy trust identified as the primary drivers of future AI adoption pace in compensation | | |
| Recruitment identified as a function with significant remaining AI growth potential | | |
| AI adoption in recruitment framed as ongoing rather than complete | AI Literacy as a Skill Being Developed | Theme 5: AI Literacy, Upskilling, and AI as a Subject of Learning Across the Bank |
| AI curated content development vendors entering the market | | |
| AI skills training emerging as the dominant learning priority across the workforce | | |
| AI literacy development through prompt engineering certification producing tangible output quality improvements | | |
| Prompt structuring as a learnable skill improving AI utility for compensation professionals | | |
| AI literacy embedded as a formal recruitment selection criterion | | |
| AI shaping what skills are valued and assessed in hiring | | |
| AI fundamentally changing the learning consumption model from compliance to engagement | | |
| Early-stage, institution-wide AI adoption | | |
| HR as a primary target function for AI deployment | | |
| AI adoption in compensation as emergent | | |
| Governance confidence and accuracy trust identified as the primary drivers of future AI adoption pace in compensation | | |
| Behind-the-scenes AI as the invisible enabler of platform quality and reliability | | |

APPENDIX VII: Research Question II Thematic Coding Analysis

| RQ2: To what extent does the use of AI automate the processes involved in the different stages of the HR lifecycle in the banking industry? | | |
|--|--|---|
| Code | Sub-theme | Theme |
| Current automation scope limited to low-complexity, high-repetition tasks | Phased Automation Logic with Mundane Tasks First | Theme 1: Automation of Administrative and Repetitive Tasks as the Current AI Use in HR |
| Administrative automation as the primary current value of AI in recruitment | | |
| Expert notes automation potential in HR, prioritising administrative tasks | | |
| Mundane task automation as the foundation for eventual higher-level AI HR capability | | |
| Phased automation with mundane tasks first as the appropriate sequencing strategy | | |
| Phased automation with simple/manual tasks first and complex tasks later | | |
| Near-term AI integration into administrative workflows a certainty | | |
| Expert notes mundane HR workflow automation will accelerate significantly in the near term | Concrete Administrative Automation Across HR Functions | |
| AI heavily automating learning administration tasks such as course data entry and roster management | | |
| AI automating platform governance and maintenance processes in L&D operations | | |
| AI automating annual course attestation workflow through replacing manual spreadsheets | | |
| Workflow automation improving L&D content governance through systematic course validation | | |
| AI automation of governance improving L&D efficiency | | |
| AI maintenance automation improving platform reliability and data integrity in L&D | | |
| Automated personalisation replacing manual learning assignment and curation in L&D delivery | | |
| New joiner mandatory learning assignment fully automated | | |
| AI reducing content curation time by automating catalogue search and skills alignment | | |
| AI-assisted pathway building enabling scalable personalised curriculum design | | |
| Process speed improvement via conversational AI as the main productivity gain in compensation administration | | |
| Manual effort reduction and workload consistency as the primary AI automation outcomes in compensation | | |
| AI automating headcount and compensation reporting | | |
| AI replacing manual system navigation and data extraction steps | Data Extraction, Reporting, and Consistency as the Automation Frontier | |
| AI automation targeting repetitive, rule-based calculation tasks in compensation | | |
| AI automating time-intensive administrative recruitment tasks | | |
| Employee-built AI agents automating self-identified repetitive tasks at workflow level | | |
| Manual L&D reporting previously consuming days of HR employee time | | |
| Old L&D reporting consisting of long manual processes now automated | | |
| Manual data extraction from L&D reports requiring multi-step human processing before AI | | |
| AI reducing L&D reporting turnaround from three to four days to a matter of hours | | |
| AI automation producing quantifiable reduction in hours spent on manual data tasks | | |
| AI speed advantage most pronounced in data-intensive operational L&D tasks | | |
| Internal AI established as the primary productivity tool that automates across the L&D team's daily operations | | |
| AI automation in data management enabling improved L&D reporting and accountability | | |
| Structured data extraction from unstructured CV documents as a concrete HR automation use case | | |
| Low-complexity data extraction tasks automatable with AI to a reliable standard | | |
| Consistency as the key criterion for trusting AI automation of routine HR data tasks | | |
| AI screening offering consistent evaluation quality across high-volume applicant pools | | |
| AI enabling end-to-end automation of basic structured information extraction and communication tasks | Measurable Time and Cost Savings | Theme 2: Quantifiable Efficiency Gains and Capacity Reallocation from AI Automation |
| AI compressing 20-week content development to a few hours representing a transformative time reduction | | |
| AI eliminating multiple sequential manual stages of the content development process | | |
| Content development automation marking a structural change in L&D production processes | | |
| AI-enabled content localisation producing direct cost savings in L&D delivery | | |
| AI replacing paid translation services for regulatory learning content localisation | | |
| AI automation delivering quantifiable time savings of 2 hours/week equivalent to a full working week per 6 months | | |
| Quantified time saving | | |
| Automation eliminating manual extraction time | | |
| AI automating L&D report analysis while human quality checks remain a mandatory step | | |
| Time savings from AI report automation enabling L&D staff to redirect effort to higher-value tasks | | |
| AI automation enabling more capacity for higher-value analytical work | | |
| AI framed as a time-buying mechanism enabling strategic reorientation of compensation team capacity | | |
| AI freeing employee capacity from data retrieval to data analysis | | |
| AI-driven process automation producing significant annual capacity gains in the compensation function | | |
| AI speed advantage most pronounced in data-intensive operational L&D tasks | Automation Gains Still to Be Realised | |
| Further automative potential yet to be fully unlocked | | |
| Automation potential highest where task repetition is greatest | | |
| Automated comprehensive compensation reporting tool as the envisioned solution | | |
| AI potential to streamline compensation analysis and data extraction | | |
| AI as an on-demand data retrieval and synthesis tool | | |
| Automation of salary benchmarking using internal data | | |

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| Platform governance quality improvement as a core outcome of AI automation | Why Humans Stay in the Loop | Theme 3: The Human-in-the-Loop: Persistent Human Involvement as a Principled Boundary on Automation |
| Human-in-the-loop as a corrective layer over automated outputs | | |
| Manual intervention retained as governance alongside AI automation | | |
| Continuous human validation even when AI automation is functioning correctly | | |
| AI automation producing grade-level errors requiring human remediation | | |
| Core recruitment judgement explicitly beyond current AI capability | | |
| Current AI automation limited to peripheral | | |
| Human contact in recruitment framed as an experiential necessity for candidates, limiting automation | | |
| Human involvement tied to outcome validity in hiring and onboarding | | |
| Appropriate and real onboarding requiring human presence | | |
| Partial automation accepted but full automation rejected on experiential grounds | | |
| Human interaction retained as a necessity for reaching the right resolution in compensation support queries | | |
| Offer negotiation identified as a human-essential recruitment task | | |
| Partial automation with AI generating, human verifying | Partial Automation in Practice | |
| Validation step retained as human requirement even after AI reduces content production to hours | | |
| Extraction and filtering stages of L&D reporting identified as automatable while final analysis retained by humans | | |
| Content creation partial automation by AI with generation automated, design and contextualisation remaining human | | |
| Human prompting needed in AI-assisted content creation | | |
| AI content generation requiring human adaptation | | |
| AI automation not displacing human candidate interaction | | |
| Partial automation coexisting with maintained human touchpoints | | |
| AI-assisted query management improving efficiency of compensation support without replacing human resolution | | |
| AI learning recommendation system being optimised to avoid redundant content suggestions | | |
| Prompt-engineered AI agent as a low-overhead approach to building interactive L&D tools | | |
| Full automation of job description generation | | Full Automation Partially Achieved / Imminent |
| Removal of human from manual job description drafting | | |
| AI eliminating the drafting stage of document production | | |
| AI automating a multi-person sequential process | | |
| Parameter-driven AI automation | | |
| Conversational AI chatbot replacing manual HR record lookup for routine employee information queries | | |
| Conversational AI chatbot enabling on-demand learning pathway guidance without human L&D consultation | | |
| Onboarding automation predicted as near-term and straightforward | | |
| Full automation of CV screening predicted as near-certain future development | | |
| Anticipated growth of AI automation in recruitment | | |
| Interview conclusion and onboarding identified as the irreducible human stages | | |
| Interview stage identified as valued and human touchpoint | | |
| Automation paradox with AI adding workload alongside reducing it | AI Adoption Adding New Tasks | |
| AI adoption generating new workflow steps not previously required | | |
| Mandated AI tool use institutionalised as a formal process requirement | | |
| Compulsory AI training adding to recruiter workload | | |
| Employee AI literacy and willingness to adopt as a prerequisite for automation benefits to materialise | | |
| AI-assisted communication as the most universally applicable daily AI use across roles | Deskilling, Identity Tension, and Human Cost | |
| AI over-emphasis in HR perceived as contradicting the function's foundational purpose | | |
| AI adoption in HR creating identity tension for HR professionals | | |
| Over-reliance on AI for response generation creating a deskilling risk in compensation professionals | | |
| AI effectiveness paradox where the better AI is at producing outputs, the less humans practise the underlying skills | | |
| Workforce AI literacy investment required while AI simultaneously reduces demand for foundational skills | | |
| AI removing the developmental tasks where recruitment skills are built | | |
| Internal AI enabling development of interactive employee engagement tools beyond existing platform capabilities | | |
| AI automation anticipated to reduce recruiter headcount through task elimination | | Job Displacement Horizon |
| AI automation anticipated to make current CV screening tasks redundant | | |
| Onboarding automation predicted as near-term and straightforward | | |
| Full automation of CV screening predicted as near-certain future development | | |
| Anticipated growth of AI automation in recruitment | | |

APPENDIX VIII: Research Question III Thematic Coding Analysis

| RQ3: To what extent does the use of AI-driven insights enhance decision-making throughout the different stages of the HR lifecycle in the banking industry? | | |
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| Code | Sub-theme | Theme |
| Explicit distinction of AI decision support from AI decision-making in daily L&D work | AI Informs, Humans Decide | Theme 1: AI as a Decision-Support Tool, Not a Decision-Maker |
| AI characterised as a reflective aid rather than a decision-making tool | | |
| AI providing informational input to human deliberation without directing outcomes | | |
| AI as an analytical input to, not a substitute for, human decision-making | | |
| AI role in HR decision-making defined as informing rather than making final determinations | | |
| Human authority over final HR hiring decisions affirmed | | |
| Human judgement and experience identified as irreplaceable in compensation decisions with AI as support tool only | | |
| AI positioned as data-driven support infrastructure rather than a decision-making agent in compensation | | |
| AI providing accurate data inputs to compensation decisions, decisions empowered but not determined by data | | |
| Compensation decisions characterised as relatively but not fully data-driven | | |
| Core decision retained by human interpretation — AI influences but does not constitute the decision in compensation | | |
| AI as data provider for human compensation decisions, the decision itself remaining outside AI's scope by design | | |
| Analytical and computational tasks in compensation automatable by AI — strategic decisions structurally excluded | | |
| Bank's AI philosophy grounded in augmentation of human capability rather than workforce replacement | | |
| Hybrid model advocated with AI driving decision accuracy through data, humans retaining interpretive authority | Where AI Assists and Where It Falls Short | Theme 2: Where AI Does Enhance Decisions: Concrete Evidence of Insight-Driven Improvement |
| Hybrid human-AI model advocated as the fairness-maximising approach to screening | | |
| AI objectivity advantage acknowledged while human contextual judgement retained | | |
| Human screening preferred over AI scoring wherever capacity allows | | |
| AI-assisted shortlisting accepted as a compromise under resource constraints | | |
| Recruiter experience overriding AI scoring output in candidate selection | | |
| AI-generated match scores insufficient basis for automated candidate elimination | | |
| Cultural fit assessment identified as beyond current AI decision-making capability | | |
| Participant doubt that AI will ever adequately assess cultural fit for recruitment decisions | | |
| AI insight accelerating mentorship programme decision-making without displacing human judgement | Human Oversight as a Non-Negotiable | |
| Future AI-streamlined HR still requiring human oversight as a fundamental design principle | | |
| Expert rejection of fully autonomous AI hiring systems with human-in-the-loop as a design requirement | | |
| Domain expertise as a necessary ingredient in AI-assisted HR decision processes, not optional validation | | |
| Human oversight framed as a risk management requirement for AI-assisted decision-making | Concrete Evidence of AI-Enhanced Decisions | |
| AI-driven learning analytics informing vendor strategy and content investment decisions in L&D | | |
| AI-assisted ideation producing successful L&D initiatives with existing evidence of decision quality improvement | | |
| AI-driven suggestions improving HR professionals' handling of difficult employee relations decisions | | |
| AI improving learning content quality through better writing, more dynamic experiences, permitting higher retention | | |
| AI-driven tools anticipated to replace third-party decision-support systems | | |
| AI as an iterative decision-support tool in L&D content design helping with questioning and refining choices | How AI Enhances Decisions | |
| AI resolving decision uncertainty by analysing options and surfacing the correct course of action | | |
| AI produces option sets rather than single recommendations | | |
| AI-generated perspectives enriching human decision-making by introducing overlooked angles | | |
| AI insight transforming curation from intuition-led to data-driven design | | |
| Decision speed improvement felt as AI decision-making benefit | Information Visibility for | |
| AI-assisted L&D reporting improving transparency and decision quality for senior stakeholders | | |

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| AI gives visibility on content quality to support decisions | | |
| AI-assisted auditing and categorisation informing platform management and governance decisions | | |
| AI filtering tool providing course selection recommendations to support L&D planning decisions | | |
| AI-generated recommendations informing human decisions for learning pathways | | |
| EU AI Act named as the primary regulatory constraint on AI-assisted HR decision-making | The EU AI Act and AI Legislation | Theme 3: AI Bias, Algorithmic Opacity, and Regulatory Constraints: The EU AI Act and the Limits of AI in HR Decisions |
| HR decision-making identified as a high-risk AI application category under existing regulation | | |
| Regulatory protection of HR decisions limiting AI-driven insight | | |
| Institutional AI governance as a structural safeguard against harmful data use in HR AI applications | | |
| LLM black-box architecture as the core technical barrier to safe AI deployment in HR decision-making | LLM Opacity, Inconsistency, and the Limits of Safeguards | |
| Shift to pre-trained LLMs removing direct control over model knowledge and decision logic in HR AI applications | | |
| Surface plausibility of AI decisions as a specific risk in HR leading to misleading confidence in outputs | | |
| 98% AI consistency insufficient for HR decisions — the 2% tail risk has disproportionate human impact | | |
| Ongoing vigilance as a permanent requirement for AI HR systems due to irreducible inconsistency | | |
| AI decision quality in HR contingent on extensive safeguards rather than model capability alone | | |
| Expert acknowledging AI decision-making capability in HR while flagging implementation complexity | | |
| Amazon hiring algorithm case study shows AI trained on historically biased data replicating gender discrimination | Real-World Harm from AI | |
| Real-world precedent of AI hiring failure demonstrating the risks of unsafeguarded deployment | | |
| AI bias in hiring producing dual harm with individual opportunity loss and organisational legal liability | | |
| AI bias mitigation potential acknowledged as a future capability rather than a current one | | |
| Ungoverned AI deployment in HR by actors without ethical considerations as a sector-wide risk | | |
| Expert warns irresponsible AI deployment in HR likely to produce significant real-world harm | | |
| AI-conducted interviews replacing human interaction flagged as a harmful trend in recruitment | | |
| AI bias risk in compensation assessed as minimal given current human-in-the-loop decision structure | Education, Confidence, and Complacency | |
| AI data risk concerns in compensation attributed to education deficit rather than substantive technical threat | | |
| System integration depth as the primary determinant of AI decision-support effectiveness in HR | | |
| Infrastructure investment in AI system integration as a prerequisite for meaningful HR decision enhancement | | |
| Human interpretive experience as a prerequisite for valid AI-assisted decision-making | Experience and Expertise as Prerequisites | Theme 4: Human Experience, Knowledge, and the Conditions for Valid AI-Assisted Decision-Making |
| Experience-dependent ability to detect AI errors in compensation data | | |
| AI insight evaluation as a learned, developmental skill | | |
| Risk of over-reliance on AI for decision-making as experienced staff exit the workforce | | |
| Professional experience and maturity identified as prerequisites for responsible AI data input decisions | | |
| Human expertise in prompting critical for extracting decision-useful AI outputs | | |
| Discrepancy identification as the human quality-control contribution in AI-assisted L&D reporting decisions | | |
| Human final review of AI outputs established as a non-negotiable step in L&D reporting decisions | | |
| AI-generated data insights requiring contextual human interpretation to be decision-ready | | |
| AI-driven insights incomplete without human contextual interpretation of underlying causes | | |
| AI as an emerging substitute for vendor-mediated data intelligence | <i>The Future Trajectory</i> | |
| Salary decisions potentially to be driven by AI in future | | |
| Compensation as a relatively lower AI-impact function compared to other HR domains | | |
| Recruitment and L&D identified as higher AI potential domains than compensation | | |