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DATA-DRIVEN DECISION-MAKING IN HUMAN RESOURCES MANAGEMENT: OPPORTUNITIES AND CHALLENGES

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Purpose: This paper examines the opportunities, challenges, and employee perceptions of data-driven decision-making (DDDM) in Human Resource Management (HRM), focusing on its impact on organizational efficiency, productivity, and engagement.
Design/methodology/approach: A mixed-method approach combines a literature review with a quantitative survey of employees in organizations using AI-enabled HR practices. Data were analyzed to assess perceptions, benefits, and implementation challenges based on established HRM and DDDM theories.
Findings: DDDM enhances decision objectivity, organizational outcomes, and employee engagement. However, adoption is limited by HR skill gaps, risks of dehumanization, and concerns about data transparency.
Research limitations/implications: The study uses a cross-sectional design with limited demographic variables. Future research should adopt longitudinal approaches and include broader factors such as industry and job roles.
Social implications: Ethical concerns—especially fairness, transparency, privacy, and dehumanization—may shape public attitudes toward workplace data use as DDDM adoption grows.
Originality/value: The study shows that employee acceptance of DDDM is driven more by ethical considerations than technological factors across all age groups, emphasizing the need for human-centered and responsible HR practices.
Keywords: Data-Driven Decision-Making, Human Resources Management.
Category of the paper: Research paper.

1. Introduction

1.1. Overview of Human Resources Management

Human Resources Management (HRM) is a strategic approach to managing employees to achieve better organisational performance (Van Vulpen, Verlinden, 2025). Bratton and Gold (2017) added that it is the strategic approach to managing employment relations which emphasizes that leveraging people's capabilities and commitment is critical for achieving competitive advantage. This means, that HRM focuses on attracting, managing, and retaining employees who actively contribute to the company's success, while ensuring they stay aligned with its strategic objectives and organizational culture (Van Vulpen, Verlinden, 2025). Contemporary literature points out that HRM brings together key basic elements: recruitment and selection, performance management, learning and development, succession planning, compensation and benefits, Human Resources Information Systems (HRIS), and also HR data and analytics (Van Vulpen, Verlinden, 2025). HRIS and HR analytics are not practices in itself but important tools of support and over the past decade, HRM has made a clear shift toward a more data-driven approach to improve outcomes and support management to make more objective decisions (Bratton, Gold, 2017). However, the adoption of digitalisation and analytics in HRM was preceded by a substantial period of transformation and gradual evolution. HRM was traditionally concerned with functional scope of managing people – it was primarily reactive and not necessarily always aligned with business goals. The function used to also be hands-on, with a focus on paper records and in-person meetings (Ankita Manekar, 2024). This often resulted in processes that could feel disjointed, especially when lacking any strategic involvement. The biggest drawback of the traditional HRM was that the teams are not always aware of what they could be doing before the organization or their employees need assistance (Jotform, 2025).

The emergence of the Fourth Industrial Revolution, known as Industry 4.0, created a need to redefine HRM in response to the demands of the new era and the term of HRM 4.0 was coined (World Economic Forum, 2019). HRM became strategic and this changed how HR departments operate, and the technology has become a major force in HRM (Prasad, 2024). Digital and social technologies advance organizational processes and the nature and meaning of works evolve. HR professionals operate in a technology-driven environment, and these technologies have replaced paper-based processes and enabled more efficient, data-informed decision-making (Cohen, 2025). Effective communication has also become central to the HR role, with clarity, empathy, and transparency emerging as core competencies (Cohen, 2025). Such change in traditional HR practices may be useful in determining how HR management systems and practices can respond to the potential opportunities and challenges associated with these changes (Connelly et al., 2021). The advancement in AI and digitization makes the process of evolution of technologies in HRM faster than ever changing

the relationship between employers, employees, and AI. Technology is being used in modern businesses, whether it is in learning and development, or management of skills by providing an innovative microlearning systems, all the way to exit interviews, employee engagement, and compensation and benefits (Tay, 2025). Therefore, HRM just like the technology is fast evolving and the academics and industry specialists speculate what it might look like. As reported by McKinsey, because of technology many roles are becoming fluid or disaggregated, and the prediction is that there will be a need for a flexible workforce defined in terms of skills with 66% of executives saying that those skills will be related to automation/digitalization (Komm et al., 2025). Among key imperatives that can help HR leaders to ready their organizations for the future identified such key components as purpose, value, culture, talent and agility, but also ecosystem which should answer question "How we grow?" (Komm et al., 2025). That ecosystem is closely linked with getting ahead by outlearning others, reaping value from data, and collaborating with HR-tech players and others in the wider HR ecosystem. Looking ahead, industry professionals hope that the future of HR will be increasingly people-centric, positioned as a strategic business partner able to help with the optimal decision-making aided by the modern technology (Cohen, 2025).

1.2. Defining Data-Driven Decision-Making

Data-driven decision-making (DDDM) constitutes a structured approach to organizational decision processes - simply saying DDDM involves utilizing data, facts, metrics and analytics to solve business problems with the key components being (Ghosh, 2023):

- data collection, which means the systematic gathering of information,
- interpretation, which is the organising and structuring of the information in a way that will be meaningful; and finally,
- analysis where data are extracted through various techniques.

DDDM is an approach that "emphasizes using data and analysis instead of intuition to inform business decisions" (Mucci, 2024). DDDM can assist in validating a course of action before the business commits to it, and the form and how it can be incorporated into decision-making process depends on individual business goals and the quality and number of data (Stobierski, 2019).

The origins of data-informed decision-making can be traced back to the early 20th century when one of earliest documented applications includes the statistical visualizations prepared by the American sociologist and civil rights activist, William Du Bois for the 1900 Paris Exposition (Bland, 2025). With his work he intended to illustrate socio-economic conditions of Black Americans and while the immediate impact of this initiative was limited, it nevertheless underscored the potential of data representation in shaping public discourse and informing policy (Bland, 2025). In the decades that followed, the development of digital technologies has facilitated widespread access to large volumes of data across sectors. Current projections suggest that global data produced by humans equals over 402.74 million terabytes daily (Mucci,

2024). This is only expected to grow, and as a result most likely influence data-processing and decision-making practices in the future.

DDDM leverages the various types of data analysis, systems and overall cognitive technologies - a term which describes "a field of computer science that mimics human brain function through a variety of means, including natural language processing, data mining and pattern recognition" (Kuzior, Kwiliński, 2022). Those technologies play a key role in DDDM because acting as tools that help extract valuable insights by analyzing data using advanced algorithms. Properly designed cognitive systems allow for the effective organization and management of vast amounts of information. These systems respond directly to the ever-growing volume of data generated. By analyzing data from various sources and reports, they increasingly support decision-making in management and streamline process management through well-designed workflows. It is being argued that every organization can benefit from integrating data into their decision-making processes by following simple steps and stages in the DDDM model (Gulia, Rastogi, 2024).

The future of DDDM is linked with what advancements occur such as the integration of AI and Internet of Things (IoT) is expected to generate powerful synergies, leading to more comprehensive and actionable insights (Sarioguz, Miser, 2024). As AI technologies continue to advance, DDDM will too increasingly involve the automation of complex decision-making tasks. Machine learning models will be capable of handling sophisticated processes, allowing businesses to automate routine decisions and allocate human resources to more strategic, high-level responsibilities. This shift promises faster and more accurate decision-making, particularly in environments that require real-time responses to large-scale data (Sarioguz, Miser, 2024).

DDDM is becoming a crucial component of contemporary business practice – this is because the strength of DDDM lies in its ability to optimize organizational efficiency and improve strategic decision-making thanks to the use of factual information (Loscher, Bader, 2023). From an operational standpoint, data use supports forecasting, inventory control, and cost optimization, enabling more precise planning in areas such as procurement and staffing (Mucci, 2024). Recent studies and academic reviews confirmed that integrating data analytics into HR processes can enhance decision accuracy, reduce biases and provide insights about workforce trends (Odionu et al., 2024). The need for organizations to use data for accurate and evidence-based decision also founds its use in HRM and the DDDM has integrated into this function.

1.3. Integration of data-driven decision-making in HRM

Data-driven solutions are increasingly recognized as potentially value-generating interventions within Human Resource Management processes (Sohani et al., 2025). However, existing analyses in an available literature review point out a discrepancy between the perceived strategic value of AI applications and their actual operational effectiveness. This is because not

many organizations feel they are ready to adopt technologies, and the actual utilization of HR analytics remains limited. The lack of readiness includes such common barriers as inadequate data infrastructure, internal resistance, and the absence of data-centric organizational cultures (Ghosh, 2025). However, at the same time the field of HRM has been a subject to transformation over the last few years and the technological advancements changed the dynamics of contemporary workplaces, putting an emphasis on need to challenge the status quo in order to remain competitive (Odionu et al., 2024). The conflict between the readiness to adopt the technological changes and the need to evolve revealed the drawbacks of the traditional HR further advertising for the need to adopt data-driven solutions.

The exact beginning of adoption of the DDDM in HRM can be difficult to pinpoint, although some research points out to the technological transformation in HR which began with the use of IT systems in the late 20th century. Initially the aim was to organize routine payroll tasks and employee record-keeping – so to automate the highly time-consuming administrative activities. As time went on when the capabilities of the systems evolved, developers began to include and expand the features such as reporting, analytics and streamlining of tasks (Gulia, Rastogi, 2024). By using those systems HR could contribute to organizational value primarily by enhancing operational efficiency, particularly through the automation of repetitive or routine tasks. It begun to empower organizations to make more informed decisions and save time in the process (Gulia, Rastogi, 2024). In this period of transformation DDDM has allowed to reshape the HRM function into strategic partner – its goal is to create a culture that uses data to make informed decisions, at the same time allowing HR processionals to align HR objectives to those of the organization (Gulia, Rastogi, 2024). Data-driven HRM, sometimes called HR analytics or people analytics, involved leveraging employee and organizational data and analytics to retain talent, drive employee engagement and improve productivity (Gartner, 2021). Data-driven HRM is enabled by various systems and platforms such as HR administrative, Learning management, and various data analytics systems systems (Gulia, Rastogi, 2024):

Further digitalization enabled through cloud-based solutions, is not only allowing automation of tasks but thanks to the integration of many functions allowed for even higher efficiency, accuracy, and instant data backups allowing HR teams to focus on core business activities and more strategic work (Purnomo, 2023). HR functions are adopting not only data analytics solutions, but also other technological advances: chatbots, AI, mobile applications, automation are the most commonly used. Chatbots for instance can be utilized to answer some routine questions regarding company policies and procedures; automation allows to delegate the previously manual tasks, like contracts drafting or scheduling of interviews, mobile applications mean real-time access to employee data, pay and leave details, benefits overviews, timekeeping recording or even learning and development. Data analytics assists with trends and patterns identification thus further assisting Business Partners and leadership to focus on strategic directions (Purnomo, 2023). Further evolution of DDDM solutions into HRM allowed

HR to utilize even more sophisticated systems and solutions such and dashboard, data visualization, predictive analytics and employee surveys adopting sentiment analysis (Purnomo, 2023).

Although, in the field of Human Resource Management, data-driven decision-making and adoption of technology can still be perceived as a disruption (Purnomo, 2023) nonetheless integration of those two fields does bring many strategic advantages to HRM. Empirical studies indicate a positive relationship between the application of analytics in HRM and organizational performance, particularly where HR strategies are closely aligned with broader institutional objectives (Odionu et al., 2024) and CIPD in their global study have found that organizations with a robust people analytics function perform better than other organizations and there is a correlation of strong business performance with strong culture (CIPD, 2018). The key to integrating DDDM with HRM from the organizational standpoint is therefore the strategic focus – development of comprehensive plans for understanding and using the data and the vast amount of it can be used to guide better decision-making (Schmidt, Olson, 2024).

1.4. Ethical considerations

In an organizational context ethics, and more precisely - business ethics, is a field which is devoted to moral issues that arise in economic activity (Orbik, 2023). As modern technology increasingly shapes what people are capable of doing, many argue that a distinct ethical framework is needed to guide its development and use, especially when assessing its broader consequences. Therefore, a concept of ethics of technology has been created to help to answer some of the questions. Technology can be used to achieve both positive and negative outcomes, depending on how its impact is being interpreted so from this perspective, hence the ethical issues linked to technology are not different from those found in other areas of human activity (Braunak-Mayer et al., 2012).

Although the use of technology has often been perceived as a more objective and impartial decision-making agent, there is growing research that challenges this assumption highlighting potential of technology to repeat or even increase biases (Tambe et al., 2019). Such cases have been well documented in recent years - for example, Amazon's AI recruitment tool discriminated against female candidates or the iTutor Group's hiring system was configured in such a way that it rejected female job seekers over 55 and men over 60 years of age (Sheard, 2025). The above examples represent so called algorithmic, and specifically training data and representation bias, and it is where existing beliefs and data would support a particular existing concept. This type of prejudice is only one type of algorithmic bias, and DDDM are also prone to (Alvi, 2025):

- Sampling bias – where dataset does not reflect the actual population, which might be a problem in recruitment tools with real-world applicants.
- Automation bias – tendency for human-makers to trust automated systems regardless if they are flawed or not, which leads to overconfidence and potentially making business decisions on subjective data.
- Confirmation bias – refers to human tendency to see evidence that confirms preexisting beliefs, for instance a recruiter may accept biased AI suggestions only because they align with their own thinking or unconscious stereotypes.

Beyond this technical bias, there are also ethical concerns. Some researchers argue that the use of AI can serve as a convenient means for individuals and organizations to evade accountability, effectively outsourcing ethically questionable decisions to algorithms. As decisions made by AI are driven by heuristics embedded within historical data, any pre-existing bias in that data is likely to be reproduced — without a clear point of human responsibility (Tambe et al., 2019). HR deals with highly sensitive and personal data so the use of analytics in this domain raises serious privacy and ethics questions and the responsible use of data is of the highest importance (The Institute of Data, 2025). Data privacy especially plays a vital role in HR decision-making as it is safeguarding employee rights, and it is aimed to ensure a fair treatment to all employees. HR professionals are bound to respect such privacy and be able to make informed and unbiased decisions. The first step to ensure proper measures, are the legal requirements placed on organizations through compliance and legislations such as GDPR in European Union. GDPR also applies in Poland and together with the Protection of Personal Data Act both governs how HR data must be handled (The Institute of Data, 2025). Non-compliance can result in severe penalties and reputational damage for the business. For instance, in 2020 H&M was fined 35.5 million Euro for their intrusive people analytics where the company was collecting data not related to employment like employee's family situation and religious beliefs without any legal basis to do so (Moss, 2025). It is evident that in line with the privacy of data transparency is also crucial. It is employees' right to know and understand how and where their data is being used, how and where it is collected and finally how it is being used, and who has access to it (Moss, 2025). There have been numerous studies done confirming that when organizations are transparent about their HR analytics practices, they are more likely to build long-term trust with their employees. Moreover, when employees receive clear information on how their information is being used the employee engagement increases by 20% in some cases, and the turnover rate is reduced by 15% (Vorecol, 2025).

Further, it is important that considerations regarding use of DDDM include:

- The need for accountability – it means that HR and managers take responsibility for their actions but also give visibility to certain outcomes, HR's role in this process is to be champions and anchor their practice to other management functions (Loscher, Bader, 2023).

- The need to balance innovation with ethics – analytics can be a powerful tool for HR professionals and organizations to make data-driven decisions related to HRM, however the need to gain insights and test innovative solutions cannot happed at a cost of responsible treatment of employees personal or sensitive information (Vorecol, 2025).
- Stemming from the above, emphasis needs to be placed on informed permission, where individuals are made aware of how their data will be used and are given the choice to opt out. Techniques such as data anonymization and aggregation should be implemented to allow valuable insights without compromising individual identities (Sarioguz, Miser, 2024).
- Finally, the need to adopt robust data security practices, including encryption, secure storage, and regular audits, help maintain the integrity of the information being used. Cultivating a culture of ethical data usage requires ongoing education and awareness within organizations (Sarioguz, Miser, 2024).

Invasive analytics or opaque data practices can erode trust - as one case study noted by SHRM showed that deploying predictive people analytics without transparency led to decreased trust among employees and that although 87% of organizations use analytics, only 19% of HR professionals believed that working with Al-analytics eliminated bias (Alexandria, 2023; Vorecol, 2025). The Institute of Data (2023) does recommend that organizations invest in specific training for ethical considerations for HR professionals so that they are equipped with knowledge and skills to make well informed and responsible decisions when dealing with data-based outcomes. Additionally, HR departments must implement robust data governance: ensuring data is anonymized where possible, used only for legitimate purposes, and protected from breaches. They also need clear ethical guidelines and communication – employees should know what data is collected and why. Cultivating a culture of ethical data usage requires ongoing education and awareness within organizations. Training programs should be established to help employees understand the ethical implications of data-driven decisions and the importance of accountability. An ethical challenge is to find a balance between analytics' insights with respect for individual privacy and fairness (Vorecol, 2025). For example, predictive models might identify an employee as a "flight risk" or "low performer" – using such insights must be handled sensitively and without bias or discrimination (Vorecol, 2025). As technologies such as AI and IoT continue to evolve, these ethical foundations will be critical for ensuring that data-driven innovation aligns with socially responsible decision-making practices.

1.5. Employee perceptions towards data-driven HRM

The integration of algorithms and technology into formal decision-making processes influences employees' experiences and behaviors (Tambe et al., 2019). It is not a new issue in the field of HRM because when the era of Scientific Management introduced systematic rules

for workplace decision-making they were often met with resistance from workers, leading to prolonged tensions between workforce and management (Tambe et al., 2019). For HRM and the business practices such as segmentation of work into simplified tasks were justified as they increased efficiency, however from the perspective of frontline employees, the situation likely resembled today's algorithmic models: decisions appeared to originate from distant departments, were presented as scientifically optimal, lacked transparency, and offered little room for feedback or adaptation (Tambe et al., 2019).

One particularly relevant concern in the context of algorithmic decision-making is its potential to disrupt established relational dynamics in the workplace between supervisors and their teams, and as a result affect trust between both (Tambe et al., 2019). This is because if, for instance, an unpopular shift is assigned by a supervisor, an employee may accept it due to accumulated goodwill or empathy for the supervisor's constraints. When the same decision comes from a software system, no such empathy or informal reciprocity is possible. The algorithm cannot be negotiated with and held accountable, which may lead employees to feel detached, powerless, and less motivated to accommodate organizational demands (Tambe et al., 2019). A study done by the 2025 Edelman Trust Barometer survey reported that 67% of employees doubt the fairness of AI-driven HR decisions, reinforcing the low trust that these tools will provide just decisions (LinkedIn, 2025). Additionally, 79% of job candidates say that they want to be informed and AI is used in hiring (Machell, 2024). A survey among over 2300 HR professionals also emphasizes a growing interest in AI and a conviction that AI in HR should support, rather than replace human judgement (SHRM, 2024). This attitude might have its origins in the publicized issues where some people experienced discrimination due to algorithmic biases, as discussed in previous chapters. Candidates lack trust is increased when supervisors are removed from processes like recruitment, because then it is uncertain whether those supervisors will exhibit the same level of commitment to new hires as they would if they had been personally involved in the selection (Tambe et al., 2019). Lack of transparency in the use of AI in key HR activities can erode trust even further. Experts emphasize that the transparency and explainability are crucial in building trust in HR analytics, and clear and honest communication about how the adopted algorithm, or technology work can alleviate that suspicion (Machell, 2024). On the other hand, it has been proven that when algorithms are capable of visibly updating in response to mistakes, they may be perceived as more legitimate (Tambe et al., 2019). Transparency can improve the acceptance of the use of DDDM - as one expert observed, when candidates see clear guidelines on how their qualifications are being assessed by an AI, it leads to a more positive perception of the hiring process (Machell, 2024). In practice, organizations that share data-driven findings and involve employees in interpreting them tend to see more buy-in. For example, a McKinsey analysis noted that companies using explainable AI and open communication achieved much higher employee adoption of HR analytics systems (LinkedIn, 2025).

The issue of trust and transparency is closely lined with concerns relating to privacy of data, specifically data collection and how it is used once stored in the organizational systems. Studies confirmed that many employees are wary of how their data might be collected and used. For instance, Deloitte found 56% of employees are concerned about the privacy implications of HR analytics, particularly regarding the use of their personal information (SHRM, 2023) Employees worry about how their data are collected and used – for instance, whether organizations monitor their emails. Academic research confirm that algorithmic HR tools can blur the boundary between workplace and personal life, leading to a feeling of constant surveillance. Employees typically cannot easily opt out of workplace monitoring, and this worry about uncertainty where employees' privacy ends can negatively affect well-being in but also outside of work (Leicht-Deobald et al., 2019).

Studies showed that employees are also concerned with the lack of human element in decision-making causing overreliance on data. What this means is that when important decisions are made solely by algorithms, this brings negative reactions from the workforce (Leicht-Deobald et al., 2019). In one experiment, participants viewed algorithmic personnel decisions as less fair and less trustworthy than human decisions, and these decisions also evoked stronger negative emotions (Leicht-Deobald et al., 2019). Academics argued that that over-reliance on rigid, data-driven rules may marginalize human sense-making, effectively crowding out employees' and managers' ability to exercise judgment or show compassion (Leicht-Deobald et al., 2019) and this can translate feeling of being treated as a number rather than a person, further fueling resistance to data-driven solutions. Another factor in shaping employee perceptions is automation of processes. Automation of HR activities decreased the percentage of time spent on transactional activities allowing to focus on transformational HR. This is what allowed the HRM to shift towards modern, strategic HRM (Bauer et al., 2023). However, from the employee's perspective it can bring worries about job security.

What became evident in recent research by CIPD is that attitudes towards DDDM in HR are also affected by the practical implications like skills and knowledge of HR professionals adopting data-driven HRM, proving that the more advanced data-driven solutions the lower is the confidence to conduct advanced analytics by HR professionals (CIPD, 2018). Such lack of knowledge and skills in data literacy is the primary barrier to adopting HR analytics (Deloitte, 2025). This skills deficit has a direct impact on attitudes: HR professionals who feel underprepared or intimidated by analytics may be less trusting of data-driven insights and more reluctant to use them. The literature describes a lack of confidence and confusion among some HR executives in how to properly adopt and leverage analytics (McIver et al., 2018). This is supported by HR professionals in organizations using people analytics, who report varying perceptions and attitudes toward data-driven HRM (Alexandria, 2023). In a recent study 82% of HR processionals said that their organization uses people analytics to assess employee retention and turnover and 71% use people analytics to assess recruitment,

interviewing and hiring. However, despite of such widely adopted use, the professionals feel that (Alexandria, 2023):

- more than half of HR executives whose organisations use people analytics say their organization provides insufficient resources to upskill HR professionals on data literacy (5 %) and to support their data infrastructure (56 %),
- only 29 % of HR professionals whose organisations use people analytics believe their organization's overall data quality is high or very high,
- staggering 95 % of HR professionals whose organisations use people analytics agree it is important to understand the rationale behind an Al algorithm's decisions, and 88 % would not trust the recommendations without this knowledge.

Industry specialist across field of HRM advocate for adoption of best practices for all those organizations wishing to adopt DDDM. They claim that in order for AI technology to be effective it must rest on strong foundations which do include not only a commitment to invest in knowledge and expertise needed to follow best practices (SHRM, 2025) such as to invest in fundamentals – amongst which the key are: an upskill HR data literacy, support data infrastructure, supply data tools and technology, quality of data, understand and be prepared to explain how people analytics is used to make decisions – transparency and elimination of the black box in rationale behind AI-aided decisions. It is also important to implement fair, ethical and responsible uses of people analytics – due to the importance the requirements for audits of systems checking for bias is slowly becoming written into regulations and mandates.

2. Methods

2.1. Research design

This study employed a mixed empirical and theoretical approach, combining a literature review on data-driven HRM with a quantitative survey of employees working in organizations that use AI-enabled HR practices. The research objectives were addressed by analyzing employee perceptions, organizational benefits, and implementation challenges through structured survey data, supported by hypotheses derived from established HRM and data-driven decision-making theory. This method was selected for its suitability and strengths such as adoption of thorough frameworks for confirming or disproving theories, the benefit of standardization, scalability and speed and finally to ensure objectivity and reproducibility for any potential future research (Lim, 2024).

Aim of the quantitative research design is to examine the opportunities and challenges of data-driven decision-making in Human Resource Management. A structured online survey was used as the primary data collection method, enabling hypothesis testing, standardized data gathering, and replicability. The design aligned with the study's objectives to:

- analyze the impact of data-driven decision-making in Human Resource Management (HRM) on organizational efficiency, employee productivity, and engagement,
- identify key barriers to the successful implementation of data-driven HRM, including skill gaps, data quality issues, privacy concerns, and resistance to change,
- explore employees' perceptions of data-driven HRM, focusing on trust, fairness, and the role of transparency in shaping their acceptance of data-driven practice.

2.2. Data collection methods

Quantitative research design offers a potential of delivering measurable results for analysis, however it has to be pointed that there are some potential shortcomings that can hinder the successful analysis when adopting this particular method. The issues may be related to a broader concept that affects contemporary social sciences today which is the connection between the pace of technological development shaping the modern world and the pace of development of research methods and contextual conditions (Komańda, 2011). In this context, engaging in online quantitative research places responsibility on the researcher not only for the design and implementation of the research procedures but also for safeguarding the individuals who participate (Komańda, 2011). To ensure respondents' privacy and confidentiality, the questionnaire did not collect email addresses or other identifying information. Although Google Forms automatically record the completion timestamp, no data such as IP addresses or geographic location were captured.

This study adopted a non-random sampling, because the research question required to focus on a specific sample group of the population. This sampling choice occurred in a judgmental and purposeful strategy and then snowballing method was selected. This practical approach allowed to reach individuals fitting the specific population of people being employed in an organization using data in their decision-making. This sampling method was preferred as it provides a starting point to explore group-specific issues, captures niche viewpoints, avoids low response rates, and is not limited by location (Qualtrics, 2025). However, to mitigate the bias in sampling a snowballing sampling was employed where study subject from several organizations recruited future subjects from among their acquaintances from the same and other workplaces alike (Lim, 2024).

3. Discussion

This study, which was based on a literature review and HR industry publications that discuss the benefits of using data-driven HR practices, examined whether effective implementation of data-driven HRM leads to improved efficiency, productivity, and engagement. A multiple regression model was performed using an implementation index, calculated as the row mean of key survey questions relating to HR efficiency, ease of using HR systems, quality of outcomes, engagement, and the impact of data quality. The analysis shows that employees generally perceive data-driven HRM as contributing positively to efficiency, ease of tasks, and performance outcomes. High agreement rates across respondents' questions indicate strong recognition of the benefits of HR technology. A majority also acknowledges that poor data quality has a clear negative impact, reinforcing the importance of reliable data for effective HR decision-making. The evidence from respondents' responses strongly supports the statement that effective implementation of data-driven HRM leads to improved efficiency, productivity, and engagement. Across multiple questionnaire items, respondents consistently reported positive outcomes associated with data-driven HRM implementation, specifically:

- 77% of respondents (39% Yes, 38% Rather yes) agreed that data is used in their organisation to improve HR efficiency. This high level of agreement affirms that employees perceive data as an enabler of more efficient HR processes.
- A combined 74.2% agreed that data helps make HR tasks easier, reflecting clear productivity benefits.
- 65.4% believe data-driven HR leads to better outcomes than traditional methods.
- 62.9% of employees perceive a positive impact on their own engagement and performance, though this is slightly lower than for efficiency and productivity. Notably, 22% expressed uncertainty, indicating that the link between data use and personal engagement may be less visible or less clearly communicated.

The findings of this study align with a growing body of literature indicating that the adoption of DDDM in HRM enhances organisational performance, particularly in terms of efficiency, productivity, and employee engagement. Empirical evidence from prior research supports this relationship. For instance, studies by McKinsey and CIPD consistently show that organisations with advanced people analytics capabilities outperform their peers in both financial performance and talent outcomes.

The study also looked at the analysis of skills and competencies of professionals responsible for using data and technology in HR. As mentioned, lack of knowledge and skills in data literacy is the primary barrier to adopting HR analytics (Deloitte, 2025). The previously cited SHRM study of almost 2300 HR professionals revelated that about 70% of respondents have experienced challenges such as employee resistance, data privacy issues and not having the resources such as a dedicated role within HR sitting with the HR IT function, to correct

algorithms (SHRM, 2024). The results of this study mirror this sentiment and show mixed levels of confidence in HR's analytical skills: while over half believe HR teams possess the required competencies, a sizable proportion disagrees or is uncertain. Privacy concerns are also divided—almost half of the respondents are worried, while a similar number are not. A strong majority indicate that transparency, human oversight, and clear explanations significantly increase acceptance of data-driven HR decisions. Preferences for traditional HR methods remain notable, with many employees perceiving that managers and colleagues favour conventional approaches. These patterns indicate that barriers exist, especially regarding HR capability, privacy concerns, and resistance to change. It must be noted that there's an overwhelming recognition (95.6% combined Yes and Rather Yes) that poor data quality negatively impacts decision-making and its outcomes. However, when placed against the multiple regression analysis the effect was found but only in a small effect:

- Only 54.8% of employees believe their HR team has the necessary data skills. A substantial 20.8% disagreed, and a high 24.5% were unsure indicating a perceived competence gap. Furthermore, "lack of skills in HR staff" was the second most frequently cited concern in Question 11, reinforcing this perception.
- 82.4% agreed that poor data quality harms decision-making, showing widespread awareness of its importance. However, the relatively low standard deviation (0.98) and small "disagree" segment (5%) indicate that this is a well-established assumption rather than a controversial issue.
- Privacy emerged as divisive. While 47.8% expressed concern, 41.5% did not. The polarisation of responses suggests that privacy is a salient but individualised concern, possibly influenced by trust in employer practices.
- 44.7% of respondents perceive a preference for traditional HR among colleagues/managers. However, 35.8% selected "I don't know," indicating a lack of awareness rather than a clear rejection of new methods. Thus, resistance appears passive or uncertain rather than active.

Finally, the study aimed to identify whether there exists a lack of human intervention as the most significant concern, followed by insufficient HR skills and the risk of bias or discrimination. Research and surveys presented by SHRM, Machell, McKinsey, CIPD and others indicate that transparency and explainability significantly increase employee trust and acceptance even though and despite concerns in this area, and as revealed by this study - a majority trust their organisations to use HR data fairly and would welcome additional transparency. Clear and regular communication was overwhelmingly seen as a way to increase trust. General attitudes toward data-driven HRM vary while a substantive group sees benefits in fairness and objectivity, others are sceptical or neutral, often due to concerns about depersonalisation or over-automation. The results indicate that negative concerns (privacy, bias, fairness) do indeed shape perceptions, while transparency, communication, and fairness significantly improve acceptance. Cconcerns over privacy significantly impact employee's

perception of data-driven HRM. Job security appears not be of a concern, and according to survey responses it has a positive outlook – this mean that according to survey respondents' data-driven can improve their sense of job security. Respondents do not feel the concern of bias is significant and it does not affect their perception of DDDM - 76.1% (48.4% Yes + 27.7% Rather yes) confirm that regular and clear communication about data usage would increase their trust in HR decisions.

Fairness is the key factor determining trust in the data-driven HRM with 33.8% of the sample confirmed that their feelings towards DDDM depends on other factors specifically how the data is used, this acceptance of data-driven HR is contingent on how it is implemented and used. Those statements reaffirmed that regular and transparent communication significantly increases employee trust in data-driven HRM.

The findings of the study indicate a positive perception of data-driven decision-making in Human Resource Management, but they also reveal significant concerns related to lack of skills in HR professionals, loss of human oversight and data privacy. Businesses can address those issues through:

- Continuous learning and development programs focused on HR analytics. HR professionals should be trained in data interpretation, ethical considerations in data use, and effective communication of data-driven insights.
- Establishing formal data governance frameworks, including regular audits and validation protocols to ensure the accuracy, completeness, and relevance of HR data. Implement data stewardship and ownership roles to oversee HR data quality and ensure compliance with organizational standards.
- A human-in-the-loop approach, especially in sensitive HR decisions such as performance appraisals, promotions, and terminations. Data should inform but not override managerial decisions, ensuring that the human aspect of HRM is preserved.
- Clear, accessible communication strategies to explain what HR data is collected, how it is analysed, and how decisions are made.
- Clear, accessible mechanisms for appealing or reviewing data-driven decisions. Through regular fairness audits organisations should ensure that fairness principles are visibly embedded in the design of HR processes and tools.

4. Summary

This paper examined employee perceptions of data-driven decision-making in Human Resource Management with a focus on both the opportunities and perceived challenges. Through a literature review, structured survey and multiple regression analyses, the research explored the effectiveness of data-driven HRM in enhancing HR efficiency, productivity,

and employee engagement, as well as factors that may influence employees' trust and acceptance of these practices.

The findings of the research confirmed that the use of data in HR processes is positively associated with perceived improvements in organizational efficiency, task productivity, and employee engagement. This aligns with existing literature emphasizing the strategic benefits of HR analytics. While the lack of HR analytics skills among HR professionals emerged as a significant barrier, other anticipated challenges - such as poor data quality, resistance to change, and privacy concerns - did not show statistically significant negative effects within the regression model. This suggests that employee perceptions may be more influenced by capability and execution than by the broader conceptual risks of data-driven systems. Concerns about privacy had a measurable negative effect on perceptions of data-driven HRM, validating the importance of ethical data handling. In contrast, concerns about algorithmic bias and job security were not found to significantly influence attitudes in this sample. Among the positive factors, perceived fairness and clear communication were important predictors of trust, while transparency alone did not yield a significant effect, emphasizing respondents' views that how data is communicated is impactful.

From the literature review and the empirical study, it can be concluded that data-driven HRM can bring both opportunities and challenges. Perceived opportunities include:

- using data to improve HR process efficiency within organisation,
- use of data in HR decisions can positively influence engagement and performance,
- regular and clear communication are crucial to increase trust in HR decisions,
- good quality data is seen as essential for realising the benefits of HR analysis.

Perceived challenges include:

- skills gap in areas such as lack of confidence and knowledge in using data analytics effectively among HR professionals,
- risk of dehumanisation mainly lack human intervention in decision-making, closely linked with:
    - over-reliance on data in as opposed to using it in line with human judgement,
    - privacy concerns and lack of transparency.

While the findings provided insight into data-driven HRM supporting research derived from the literature review, several limitations must be acknowledged. The research relies on self-reported data of non-random convenience sample, which may be subject to response bias or inaccuracies that could come from employees' knowledge of internal HR systems. The study was performed as one-time research therefore it does not provide further insight about of how perceptions could evolve over time. The sample was largely composed of educated and younger respondents, which may not fully reflect the broader workforce diversity. The analysis included age as a demographic factor, other potentially influential variables such as a job role, specifically managerial versus non-managerial positions, organizational size or industry were

not included in the data collections. These limitations suggest caution in generalizing the results beyond the studied context.

Future research could explore the development of employee perceptions over longer periods of time. Studies could also investigate sector-specific or role-specific attitudes, particularly among blue-collar or frontline employees. Future research could be supported by qualitative methods such as interviews and focus groups as it could provide deeper insight into how employees interpret fairness, privacy, and managerial transparency in real-world HR decisions.

In summary, this study confirms the potential of data-driven decision-making in Human Resources Management within organizations at the same time emphasizing the importance of employee-centered implementation. Data-driven decision-making may offer opportunities for improving fairness, efficiency, and strategic alignment in HR practices. However, its successful adoption ultimately relies on employee trust, ethical safeguards, and the preservation of human judgment. In recognizing these conditions, organizations can more effectively leverage HR analytics to build not only more efficient but also fairer and more inclusive workplace.

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