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Enhancing Employee Performance Management Through AI-enabled Predictive and Decision-Making Models

A Thesis Submitted in Partial Fulfilment of the Requirements for the Doctor of Philosophy Degree in Business Analytics

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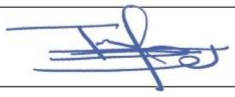
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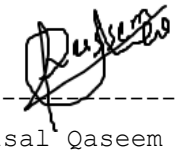
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ABSTRACT

Improving employee performance management is essential to achieving organizational excellence, especially in the public sector, where limited resources, bureaucratic constraints, and rising citizen expectations demand innovative solutions. This thesis addresses the challenge of enhancing employee performance management in Bahrain's public sector by integrating advanced AI-driven predictive and decision-making models. Using a sequential exploratory mixed-methods design, the research first conducted a systematic literature review and qualitative inquiry. Expert interviews and focus groups distilled 54 potential performance factors into 46 context-specific determinants tailored to the Bahraini public sector. Then, a follow-on quantitative phase: a structured survey was administered to a simple random sample of 391 Bahraini public employees, yielding data to train machine-learning models. In line with an exploratory sequential design, beginning with qualitative exploration to develop a quantitative instrument, this approach ensured that the predictive model was grounded in a real organizational context and theory.

Based on the refined determinants and historical performance data, an AI-based predictive system was developed. Empirical results demonstrate that the model accurately forecasts employee performance outcomes and identifies performance gaps. In particular, a Support Vector Machine (SVM) classifier achieved 92.51% accuracy in distinguishing high vs. low performers, confirming the framework's efficacy. Other classifiers also showed strong predictive power, and employing genetic algorithms for feature selection further improved performance by optimally selecting relevant variables. To make the AI system actionable for HR decision-makers, we incorporated explainable-AI techniques. Tools such as SHAP (Shapley Additive Explanations) provided global and local interpretability of the model's outputs, revealing the relative importance of each performance factor and enabling translation of predictions into targeted policy insights.

The thesis contributes a novel, replicable paradigm that bridges traditional HR practices and cutting-edge AI, transforming performance appraisals into continuous, data-driven processes. In practice, these findings lead to concrete recommendations, most notably the establishment of transparent AI governance and ethics policies, upgrading HR data infrastructure and gradually integrating validated AI models, and aligning AI initiatives with Bahrain's national digital strategy, as Bahrain's Vision 2030 and its updates 2050.

DEDICATION

This thesis is dedicated to my parents, whose unwavering support and encouragement have guided my academic journey. Their steadfast belief in education's transformative power and tireless efforts to nurture my character have profoundly influenced my personal development. Their guidance and affection have fortified me to persevere through challenges and remain committed to achieving this goal. In addition, I would like to express my profound gratitude to my close relatives, including my wife, children, siblings, sister, and close friends, whose tolerance, encouragement, and unwavering trust in my capabilities have been a constant source of motivation throughout my journey. May this success forever serve as an eternal testament to my parents' enduring legacy and my beloved relatives' unwavering support.

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PUBLICATIONS

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence

ML – Machine Learning

DM – Data Mining

GA – Genetic Algorithm

EPM – Employee Performance Management

PSM – Public Service Motivation

EI – Emotional Intelligence

OCB – Organizational Citizenship Behavior

JD-R – Job Demands–Resources

LMX – Leader–Member Exchange

HPWS – High-Performance Work Systems

RBV – Resource-Based View

TAM – Technology Acceptance Model

PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses

SLR – Systematic Literature Review

KPI – Key Performance Indicator

KNN – K-Nearest Neighbors

RBF – Radial Basis Function (in the context of SVM kernels)

SVM – Support Vector Machine

SHAP – SHapley Additive Explanation

Chapter 1
Introduction

1.1 Overview

Employee performance continues to stand at the forefront of organizational success and strategic management (Aguinis, 2019; Armstrong, 2015). This is particularly evident in the public sector, where the interplay between resource constraints and increasing citizen expectations heightens the importance of cultivating high-performance cultures. In the Kingdom of Bahrain, the public sector drives national development and ensures the provision of essential services, placing added emphasis on effective performance management systems. These systems must account for the complexities of a dynamic socio-cultural environment, address the pressures of digital transformation, and respond to evolving work models that demand greater transparency and adaptability.

Within the scholarly landscape, numerous studies have outlined a wide range of factors that can influence employee performance, ranging from leadership and organizational culture to technological infrastructure and regulatory frameworks (Tranfield et al., 2003; Webster and Watson, 2002). However, these factors do not necessarily carry equal weight across different cultural or institutional settings. In Bahrain's public sector, the interplay of unique administrative policies, cultural practices, and emerging e-government initiatives calls for a tailored examination of performance determinants. To meet this need, the present study began by undertaking a systematic literature review that identified 54 potential factors, subsequently refined through expert interviews and focus group discussions into a final set of 46. These factors were then classified into

seven thematic domains, ensuring alignment with local public-sector imperatives and expert consensus (Barbour, 2018; Creswell and Creswell, 2018).

A core contribution of this work is the linkage of these refined factors to advanced analytics, specifically AI-based predictive and decision-making models. While considerable research has explored the underlying determinants of performance, there remains a gap in applying these determinants to the design and implementation of innovative, data-driven tools. This study highlights practical avenues for optimizing performance management in the Bahraini public sector by mapping each of the seven thematic domains to relevant AI applications. The emphasis on AI reflects global trends in human resource analytics and responds to Bahrain's broader digital transformation strategies, offering a way to enhance decision-making processes and resource allocations.

Ultimately, this review synthesizes both international insights and local contextual analysis, striving to close knowledge gaps in how public-sector performance factors can be systematically identified and applied to emerging technologies. It also sets the stage for more sophisticated performance management approaches, giving policymakers, HR practitioners, and organizational leaders an evidence-based framework for fostering excellence, adaptability, and sustainability within the Bahraini public sector. This integrated approach underscores the critical importance of context-specific research and lays a strong foundation for future inquiries into AI-driven performance management solutions.

1.2 Background of the Problem

In recent years, employee performance management has garnered significant attention from organizations around the world for its critical role

in driving organizational success. The process involves aligning individual employee goals with those of the organization, regularly evaluating employee performance, and providing appropriate feedback to improve performance (Aguinis, 2019). The public sector faces unique challenges and expectations, making effective employee performance management increasingly important for public organizations (Kroll, 2015). Public sector organizations face challenges such as limited resources, bureaucratic constraints, and balancing the interests of different stakeholders (Pollitt and Bouckaert, 2017). With higher scrutiny and transparency expectations from the public and media, improving employee performance is critical to ensuring the efficient use of resources and achieving organizational goals (Kroll, 2015). Traditionally, the private sector has focused on setting individual goals, performance reviews, and rewards (Armstrong and Baron, 2005), but recent studies show that a more holistic and ongoing approach is needed. Due to the changing nature of work and the increasing importance of teamwork and collaboration to organizational success (DeCenzo et al., 2021), this approach should include regular feedback, employee engagement and development opportunities (Pulakos et al., 2015).

Although the public and private sectors differ in operating environments, they face similar employee performance management challenges. These challenges include setting clear and measurable performance goals, providing constructive feedback, and balancing individual and team performance (Risher, 2015). In addition, organizations in both sectors must address the issue of performance appraisal bias and the potential negative impact of performance appraisals on employee motivation and engagement (Murphy and Cleveland, 1995). Artificial intelligence (AI) and machine learning have brought about significant

changes in human life resource management. This advancement has led to innovative approaches to increasing employee performance. AI-powered predictive modeling and decision-making have significant potential to improve employee performance management in the public sector. By analyzing data from various sources such as key performance indicators, employee feedback and historical trends, AI systems can objectively and accurately assess employee performance (Chen et al., 2012). As a result, this can lead to better performance assessments, targeted development plans, and AI-driven decision-making that can ease the task of public sector organizations in resource allocation and workforce planning (Manyika et al., 2021).

AI-enabled predictive modeling uses machine learning algorithms to analyze historical data and identify patterns that can help predict future outcomes and make decisions (Brynjolfsson and Mcafee, 2016). In the context of human resource management, predictive models can be used to predict employee performance, identify skill gaps, and design targeted interventions to fill these gaps (Marler and Boudreau, 2017). By leveraging vast amounts of data and sophisticated algorithms, AI systems can provide insights that would be difficult for humans to detect or analyze manually (Nguyen et al., 2015). Recent studies have shown the potential of AI-supported decision-making in human resources, such as that of (Arora et al., 2021; Fallucchi et al., 2020; Gélinas et al., 2022; Wu and Shang, 2020). However, there is still much to be explored, particularly in the context of the public sector.

1.3 Statement of the Problem

Bahrain's public sector plays a vital role in the country's economy, providing a wide range of services such as education, healthcare, and public infrastructure. The number of government employees is estimated

at 41,000 (Akhbar-Alkhaleej, 2024). Therefore, understanding the challenges associated with performance management of Bahrain's public sector employees is necessary to improve performance delivery and efficiency.

The Bahraini government has made a significant effort to develop performance management methods for public employees through the Civil Service Bureau, but systematic assessment and feedback methods are still lacking. By focusing on evaluating short-term performance and linking it to annual quota incentives, employees can become dissatisfied and thereby lose motivation (Hassan and Aljawder, 2020). In addition, there is no effective performance management system that aligns individual performance with strategic public-sector objectives. Therefore, it is challenging to identify areas for improvement and allocate resources effectively. There is also a need to review and improve the evaluation process to align it with the organization's vision and mission (Abu Shanab et al., 2021; Hasan and Hassan, 2021). Additionally, the public sector faces difficulties in attracting and retaining high-quality employees due to limited advancement opportunities, low employee engagement and uncompetitive compensation packages due to austerity measures and economic factors. Moreover, public sector goals are more diverse and less tangible, resulting in more difficult implementation of talent management practices (Kravariti et al., 2022).

In recent years, the use of artificial intelligence in Bahraini’s government sector has increased. Due to the Kingdom's efforts to modernize its services to make them more efficient and reliable, artificial intelligence has become necessary in various areas of the Kingdom. Bahrain is not the only country undergoing a shift toward artificial intelligence. There has been a global shift towards artificial intelligence to

replace human power in modern organizations with more efficient and sustainable machine-based systems. Taking them into account, artificial intelligence could serve as a powerful engine for economic growth by offering decision-makers a unique machine-based perspective free from bias. This is all in line with the vision and goals of Bahrain's Economic Vision for 2030 (Seyadi et al., 2021).

Despite the growing interest in AI applications in HR and performance management across a variety of industries (Brynjolfsson and Mitchell, 2017; Palos-Sánchez et al., 2022), there is a lack of research on AI-driven performance management tailored to specific industries in the context of Bahraini public sector. This knowledge gap hampers the effective use of AI technologies to improve employee performance management in the public sector. AI-powered predictive modeling and decision-making in the public sector could address the above challenges by enabling better alignment between individuals and organizations. Achieve goals, enable more effective resource allocation, and enable more accurate and data-driven performance assessments (Wu and Shang, 2020). The research problem outlined in this study will benefit public sector organizations in Bahrain and further the understanding of AI-driven performance management in the public sector in general.

1.4 Research Questions

The research question to be addressed in this study is: How can AI-enabled predictive and decision-making models enhance employee performance management in the public sector in the Kingdom of Bahrain? The research question can be broken down into the following sub-questions:

RQ1: What are the key factors affecting employee performance in the Bahraini public sector?

RQ2: To what extent are the proposed machine learning models effective and accurate in predicting employee performance by leveraging drivers of employee performance in the Bahraini public sector?

RQ3: How can AI-assisted decision-making models help improve employee performance in the Bahraini public sector?

RQ4: What practical and ethical aspects should be considered when implementing AI-driven performance management tools in the Bahraini public sector?

1.5 Research Objectives

The primary objective of this research endeavour is to investigate the potential of AI-enabled predictive and decision-making models in enhancing employee performance in the public sector in the Kingdom of Bahrain. To achieve this objective, the research will aim to achieve the following specific objectives:

RO1: Identifying the key factors influencing the performance of employees in the Bahraini public sector, examining the unique characteristics and challenges of the regional context.

RO2: Building a machine learning-based predictive model to predict employee performance in the Bahraini public sector.

RO3: To evaluate the effectiveness of the developed predictive model in predicting employee performance in the Bahraini public sector, measuring its impact on various performance metrics.

RO4: Exploring and identifying AI-based decision-making models that potentially improve employee performance in the Bahraini public sector, by comparing their feasibility and efficiency based on context-specific criteria.

RO5: To shed light on the ethical and practical considerations associated with implementing AI-enabled performance management tools in the Bahraini public sector and highlight the importance of responsible and transparent use of these technologies to mitigate adverse consequences and promote fair human resource management practices.

1.6 Research Significance

The importance of this research lies in the potential benefits that AI-enabled predictive models can offer to the public sector in Bahrain. This study develops and evaluates an employee performance model that takes into account the unique context and factors affecting employee performance in the selected public sector. It is expected that this dissertation will contribute to the following areas:

1. A better understanding of the factors affecting the performance of public sector employees in Bahrain in order to develop more effective human resource policies and practices. This is consistent with the findings of Aguinis and O'Boyle (2014), who found that a better understanding of the factors influencing employee performance can lead to the development of more effective HR policies and practices.
2. Developing effective predictive tools to predict employee performance in the Bahraini public sector and identifying effective models for the decision-making process in this regard will contribute to the ongoing discussion regarding how artificial intelligence may impact the workplace, particularly for the public sector. This is consistent with the work of Brynjolfsson and Mitchell (2017) and Chui et al. (2018), who have argued that AI has the potential to considerably affect work in both the public and private sectors.
3. Provide valuable insights into the practical and ethical implications of implementing AI-driven performance management tools in the public

sector and promoting the responsible and transparent use of these technologies. This is consistent with the work of Dignum (2019) and Müller and Bostrom (2016), who have argued that it is important to consider the practical and ethical implications of AI-driven performance management tools before implementing them.

1.7 Ethical Statement

All ethical issues have been carefully addressed to obtain reliable data from the population sample. All interested parties have been contacted in advance to obtain their approval. In addition, no personal information of the respondents will be disclosed as part of the survey in this research. The researcher took a number of initiatives to ensure the study maintains an ethical balance. Participants were first informed of the purpose of the study before their consent was obtained. All respondents were guaranteed anonymity, and no personal data was collected. In this study, respondents' identities associated with the public sector in which they work remain anonymous. During the survey process, the researcher refrained from asking personal questions. Each survey was accompanied by an agreement and an information sheet to enable all respondents to participate. The researcher ensured that all respondents were willing to participate voluntarily by signing the questionnaire and reading the introduction, including the ethical agreement specified in the questionnaire.

Chapter 2
Literature Review

2.1 Overview

Employee performance management (EPM) has been recognized as a crucial contributor to organizational success, particularly within the public sector, due to the necessity for efficiency, accountability, and the delivery of a high standard of service. This chapter offers a thorough overview of the existing literature on EPM, covering the historical context, theoretical foundations, and the factors that affect its implementation. The presentation is structured so that it first establishes a foundation of performance management approaches, offering an overview of historical and contemporary approaches, and elucidates their continued relevance in the present day.

The chapter commences with an outline of the evolution of EPM, tracing it back from Frederick Taylor's scientific management theories to contemporary strategic performance models that blend data analysis and technology. A range of concepts of EPM are explored, indicating the transition from performance appraisal models towards holistic models aimed at continuous development, employee commitment, and organizational goal setting. A systematic review has been conducted to identify the determinants of employee performance through a comprehensive review of relevant studies from Scopus, Web of Science, JSTOR, and Google Scholar has been undertaken to ensure an exhaustive, rigorous, and evidence-based approach. Emerging trends, such as the utilization of AI in performance evaluation, efforts towards digitalization, and HPWS, have also been incorporated into the study. Given Bahrain's

ongoing modernization plans under Vision 2030, the chapter also anchors international findings in the Bahraini public sector, discussing the unique opportunities and challenges confronting performance management. The overview emphasizes the need for predictive, AI-enabled models to boost employee performance and human capital development strategies. In conclusion, this chapter establishes the foundation for empirical study by providing a theoretical context and evidence-informed strategies, outlining an approach rooted in data towards strengthening performance management in the public sector.

2.2 Employee Performance Management

Employee performance management (EPM) is a broad and complex concept that has been defined in a variety of ways by different scholars and practitioners. According to Aguinis (2019), EPM is "a continuous process of identifying, measuring, and developing the performance of individuals and teams and aligning performance with the organization's strategic goals". This definition underscores the cyclical and dynamic nature of EPM, emphasizing its alignment with organizational strategy. Nevertheless, it has been contended by several scholars that this characterization is overly restrictive, failing to encompass the comprehensive array of activities and objectives inherent to EPM. For instance, Brown et al. (2018) provided a more expansive definition of EPM, identifying it as a process of employees' performance management through various HRD interventions formally and informally to enhance the performance level of individuals and groups. The definition acknowledges that EPM is a measurement and developmental process with multiple learning modes such as mentoring, coaching, training, and giving and taking feedback. Accordingly, EPM is significant in the area of human

resources development (HRD) in the sense that it can build employees' competencies and abilities and also motivate and gratify them.

2.2.1 Historical Overview of Performance Management

Employee Performance Management (EPM) has been drastically transformed since the beginning of the 20th century. Frederick Taylor's scientific management in the early 1900s marked the beginning of systematic evaluation and performance enhancement. In its initial versions, EPM was primarily concerned with performance appraisal: a measurement of employees following predefined goals. By the onset of the 20th century, managers made subjective ratings in order to decide on compensation, and in the 1930s, there was a move towards more systematic rating scales and forms. In World War II, performance appraisal gained increased usage in the United States federal government in order to inform personnel choices (Aguinis, 2019). However, most of these initial systems later received criticism for their low validity and even negative implications for employees' motivational levels. Consequently, there was a move back towards creating better strategic approaches.

A significant movement in such a transition was the introduction of management objectives in the 1950s, where employees and supervisors worked together to define goals by organizational strategy (Smither and London, 2009). By the 1980s, performance management was not only about goal setting and performance feedback but also about reward systems and growing recognition of organizational elements driving performance (Denisi and Murphy, 2017). The contemporary-day models of EPM are even more comprehensive in design, with a combination of developmental support, goal alignment, and technology-driven processes. These systems leverage metrics, mentoring, and regular feedback, often with the support of analytics, in order to drive decision-making and improve performance

in general (Brown et al., 2018). The holistic perspective is aimed at developing a highly motivated and highly skilled workforce and, in doing so, attaining a source of enduring competitive advantage.

Continued research is aimed at better-developing goal alignment, capitalizing on emerging technologies, improving performance measurement tools, and greater employee involvement, all working together to leverage the global implementation of EPM better. When underpinned by a supportive organizational culture and transparent processes, EPM systems have been demonstrated to drive improved organizational and individual performance. It supports the transition of EPM to a core strategic role beyond appraisals and drives ongoing development, skill-building, and longer-term performance.

2.2.2 Factors Influencing Employee Performance

2.2.2.1 Research Strategy

The research study adopted a systematic review of the literature approach to establish factors affecting employee performance in the public sector. This approach integrated information from various respected scholarly sources, captured a wide range of findings, and ensured the study was kept within the purview of global and regional research perspectives. In this respect, a literature search was comprehensively carried out through Scopus, Web of Science, JSTOR, and Google Scholar, which are high-impact databases with extensive coverage of peer-reviewed research in the fields of public administration, organizational behaviour, and human resource management. In this regard, during the process of searching, only specific Boolean operators and keywords such as "employee performance," "public sector," "performance factors," "performance appraisal," "employee performance management," "public service motivation," and

"knowledge sharing" in streamlining the search to keep a clear focus (Petticrew and Roberts, 2006).

A search string was therefore constructed, based on these parameters, in the format: "employee performance" OR "work performance" OR "job performance" AND ("factors" OR "determinants" OR "influencing") AND ("public service" OR "public service motivation" OR "training" OR "workplace"), thus returning a wide results set on the first attempt. The eligibility of each choice was strictly based on adherence to the PRISMA framework, guaranteeing the consideration of many sources, allowing both improved transparency and, thus, increased reliability (Page et al., 2021).

This initial identification came up with 1,200 articles; after removing duplication, 1,000 unique records had been identified and required review. After a title and an abstract screening, 650 non-inclusion criterion-compliant articles had been excluded. This had narrowed the count further to 350 articles at the eligibility stage, as seen in Figure 2.1, wherein the remaining articles' full texts had been screened against the inclusion and exclusion criterion of either lacking a public sector-focused attention span and failing the minimal standards of methods and not being highly relevant at the review query level. Ultimately, 108 of the remaining articles had passed the inclusion and exclusion tests and were eligible for final review. Only 2018-2024 had been the inclusion criterion for evaluating the final set of the remaining 108 articles if they had been indexed in reputable sources such as Web of Science and Scopus. The inclusion of non-employee metrics-focused articles, non-indexed and predator sources, and non-public sector-focused subject matters had been excluded from this review. The technical processes-focused studies that had not been concerned with human performance factors had also been excluded. This

was a strict screening process, as seen in Table 2.1, that was performed to ensure the final set of 108 articles had the required methodological and contextual significance to support the study objectives.

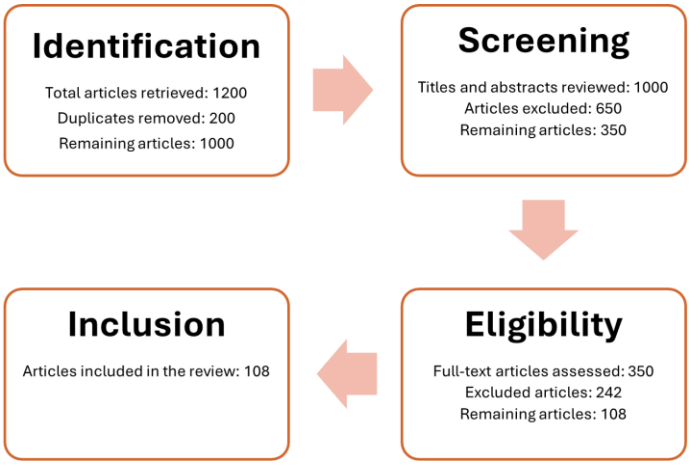


Figure 2.1: PRISMA Flowchart for Article Selection

These papers were systematically analyzed with the intention of extracting critical information ranging from underlying theories of performance such as Maslow's Hierarchy of Needs and the Job Demands-Resources Model to specific quantitative findings pertaining to factor-performance correlations.

Table 2.1: Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication Date	2018 to 2024	Studies published before 2018
Peer-Review Status	Peer-reviewed articles indexed in Scopus, Web of Science, or equivalent databases	Non-indexed or predatory journal publications
Focus	Studies addressing factors influencing public sector employee performance	Studies unrelated to public sector contexts or focusing on non-organizational performance metrics

Criterion	Inclusion	Exclusion
Language	Articles available in English	Articles in languages other than English
Relevance to Study	Articles demonstrating clear relevance to public sector employee performance, supported by theoretical or empirical evidence	Articles focusing on irrelevant factors, such as non-human technological applications or non-organizational outcomes
Methodological Rigor	Articles employing robust methodologies, including case studies, surveys, and longitudinal analyses	Studies with methodological limitations or insufficient details

It strongly emphasizes qualitative insights, especially those related to nuances in implementing performance-enhancing measures in public-sector contexts. The reviewed methodologies included case studies, surveys, and longitudinal designs. The information extracted was organized into recurring themes, such as job satisfaction, knowledge sharing, organizational culture, and public service motivation, thereby enabling a coherent narrative synthesis of the data. Because of this heterogeneity in methodologies, a narrative synthesis approach was adopted to synthesize findings and explore conflicting or context-dependent conclusions. Whereas many studies stressed job satisfaction as a universally relevant construct, for instance, others related its effects to specific cultural or organizational contexts.

2.2.2.2 Factors Influencing Employee Performance: Comprehensive Thematic Overview

A systematic literature review was conducted according to the stated criteria to identify critical performance factors that can be used to explain employee performance. A total of 54 factors were extracted, each critical

in determining employee behaviour, motivation and productivity at the organizational level. These factors came from varied theoretical frameworks and empirical findings drawn from global and regional research perspectives. The factors were then organized into thematic groupings to provide clarity and coherence to the findings. The factors, definitions, key supporting references, and observed impacts on employee performance are identified below.

Behavioral and Motivational Drivers

Behavioural and motivational factors, including public service motivation (PSM), job satisfaction, organizational commitment, proactive behaviour, organizational citizenship behaviours (OCBs) and employee autonomy, have been identified as fundamental determinants of employee performance.

Public Service Motivation (PSM) is defined as an individual's tendency to respond to motives that are primarily or exclusively grounded in public institutions and organizations. The conceptual underpinnings of PSM are rooted in the seminal framework developed by Perry and Wise (1990), which emphasizes altruistic and pro-social behaviours directed towards serving the public interest. A meta-analysis by Sudha et al. (2023) indicates that higher levels of PSM are associated with increased job satisfaction and improved job performance among public sector employees. Furthermore, Zhang (2023) found that PSM positively influences job satisfaction by decreasing role overload, with marital status moderating this relationship.

Job satisfaction is defined as the extent to which employees are pleased with all aspects of their jobs, including the tasks they perform, the environment they work in, and the compensation they receive. Herzberg's Two-Factor Theory (1959) differentiates between 'hygienic factors',

encompassing conditions of work and salary, and 'motivators', including recognition and achievement, in determining job satisfaction. Consequently, Min et al. (2021) conducted a meta-analysis estimating that there exists a statistically significant positive correlation between job satisfaction and performance, meaning satisfied employees produce more, are more industrious, and are attached to organizational goals.

Organizational commitment can be defined as the level of psychological commitment and loyalty that an employee shows towards his or her organization. In an effort to understand and influence employee performance in the public sector, organizational commitment emerges as a critical factor (Tantra et al., 2024). The three-component model proposed by Meyer and Allen (1991) provides an explanation for a set of these dimensions in terms of their effects on work behaviour and performance outcomes. This model identifies three distinct dimensions of organizational commitment: affection, continuity, and normative commitment. Higher levels of organizational commitment are associated with higher employee productivity, job satisfaction, and lower turnover rates (Harahap et al., 2024). It is believed that employees who feel a high level of commitment to their organization are more likely to align their personal goals with the goals of the organization, thereby increasing their performance (Ying et al., 2024). Additionally, transformational leadership has been identified as a mediator in the relationship between organizational commitment and performance, suggesting that effective leadership practices are essential for promoting commitment (Wonda, 2024). Therefore, it is necessary to develop strategies that strengthen organizational commitment to maintain high employee performance in the public sector.

Proactive behaviour is defined as self-initiated and future-oriented action to change or improve the situation or oneself. Bateman and Crant

(1993) state that proactive behaviour is "a self-initiated discretionary workflow of an individual that is also future-oriented, with the intent of changing and improving either the self or the environment". Proactive employees in the public sector take the initiative by anticipating issues and finding solutions, leading to organizational effectiveness. A recent study by Wang et al. (2024) has shown that proactive individuals are more engaged in behaviours that contribute to better performance, thus emphasizing the importance of fostering a culture of proactive working in organizations. Additionally, employees who are encouraged to adopt a more proactive approach to their work report higher levels of job satisfaction and performance, underscoring the need to promote a culture of proactive working in organizations.

Organizational Citizenship Behaviours (OCBs) are defined as discretionary actions by employees that positively contribute to organizational functioning. The concept was introduced by Organ (1988), who described OCBs as behaviours that enhance the social and psychological environment of the workplace. These behaviours include altruism, conscientiousness, sportsmanship, courtesy, and civic virtue. Recent studies have demonstrated a positive relationship between OCBs and employee performance. For instance, the survey conducted by Widayati et al. (2020) indicates that OCB has a positive impact on employee performance, suggesting that employees who frequently engage in OCBs are more likely to perform better in their roles. Furthermore, a study by Bustomi et al. (2020) corroborates the assertion that OCB exerts a considerable influence on employee performance, with their findings indicating that a substantial proportion of organizational performance variation can be attributed to OCB. Similarly, employee autonomy is the degree of freedom and discretion an employee exercises in their work. It is

based on the Job Characteristics Model postulated by Hackman and Oldham (1976). It is a fact that employee autonomy is vital for motivation and satisfaction. This leads to better performance because employees can relate more meaningfully to their jobs. Autonomy is a crucial driver of performance, motivating employee innovation and intrinsic motivation (Demircioglu and Chen, 2019). This autonomy provides the individual employee with the professional freedom to make decisions, which is critical for efficiently managing complex citizen-centred services. More job autonomy correlates with increased job satisfaction and productivity (Ciobanu et al., 2019); hence, it is crucial to organizational success within the public sphere.

Skills and Competencies Factors

Employee competencies are pivotal to enhancing performance in dynamic environments. This includes emotional intelligence (EI), communication skills, knowledge-sharing ability, cognitive abilities, competence, adaptability, employee resilience and digital literacy and skills.

Emotional intelligence, as defined by the seminal work of Mayer et al. (2016), can be understood as the ability to perceive, understand, and manage one's own emotions and the emotions of others. Goleman (1995) later overemphasized the concept in a working environment, including self-awareness, self-regulation, motivation, empathy, and social skills. Empirical evidence shows that employees with higher EI have stronger interpersonal relationships, manage stress better, and make better decisions, consequently performing better at work (Zampetakis and Mitropoulou, 2024). It is clear that EI is positively related to teamwork, lower turnover intentions, and leadership effectiveness (Kiishi, 2024). This unequivocally demonstrates that the more an organization invests in

developing emotional competencies among its employees, the better the organizational outcomes are.

Communication skill is defined as the clear and effective imparting or conveying of information. Indeed, as posited by Burks et al. (1951) communication model, communication has been identified as the cornerstone of organizational success. This is due to the fact that effective communication reduces the likelihood of misunderstandings by ensuring that the message is communicated with clarity. In the context of public service, the enhancement of communication skills has been shown to foster cooperation, amplify transparency, and optimize service delivery. A study by Gbarale and Lebura (2020) posits that institutional communication, particularly its vertical form, exerts a profound influence on employee performance. Consequently, it is imperative that public sector organizations invest in the development of robust professional communication channels. Communication skills are important in fostering trust and a positive work environment, and they are instrumental in enhancing employee performance. This finding is further supported by the notion that organizational knowledge-sharing abilities foster collaboration and innovation. The degree to which individuals within an organization can share information, expertise and skills is indicative of the level of knowledge-sharing within the organization. According to the Social Exchange Theory proposed by Blau (2017), such exchanges foster the development of trust, thereby encouraging employees to be more receptive to the concept of reciprocity. A study by Kim et al. (2024) established that knowledge-sharing behaviour significantly impacts innovative work behaviour, increasing one's job performance. Moreover, Nguyen et al. (2020) demonstrated that the influence of knowledge sharing with two central processes, namely knowledge donation and knowledge gathering,

on innovative work behaviour was significant among public Vietnam Telecommunications employees, thereby showing how vital knowledge-sharing is in building a committed workforce.

Cognitive abilities are mental capabilities such as reasoning, problem-solving and planning. The g factor, or general intelligence, is a core determinant of cognitive performance, as Spearman (1904) definitively established. Research shows that higher cognitive abilities strongly predict job performance across various occupations. This is because they facilitate the acquisition of job-related knowledge and efficiently execute complex tasks. A meta-analysis by Nye et al. (2022) definitively found that cognition-related abilities positively correlate with job performance, particularly in positions that demand advanced reasoning and problem-solving abilities. Cognitive ability is undoubtedly one of the most powerful predictors of job performance across various industries and occupations. An individual's cognitive endowment positively correlates with job performance, including productivity, flexibility, and leadership potential. Similarly, Competence is the combination of an individual's skills, knowledge and abilities in executing tasks. According to Boyatzis (1982), competence is defined as an underlying characteristic of a person that is causally related to the adequate performance of a job. In public service, employees' competence is critical in delivering quality service and achieving organizational objectives. Competence and performance are directly related and frequently influenced by factors such as motivation and organizational culture. A study conducted by Yulius (2021) demonstrated that, although motivation and competence are both crucial factors, competence has a more pronounced impact on performance than motivation alone. Prioritizing the improvement of employee competencies is a key strategy for enhancing performance. Investing in employee

competence benefits the individual and contributes to collective performance. It supports the larger objectives of public sector organizations and improves service outcomes for the community.

Adaptability is defined as the degree of a person's readiness to enter new conditions and effectively respond to any work change. Ployhart and Bliese (2006) have theorized adaptability as one of the most vital competencies for performance in dynamic environments. In the context of the public sector, characterized by the perpetual evolution of policies and the scarcity of resources, the adaptability of employees assumes paramount importance. For instance, Park and Park (2020) found that employees who are adaptable are more likely to accept organizational change and, consequently, demonstrate superior performance. Adaptable employees are able to develop effective coping strategies in response to organizational changes, and this, in turn, leads to better job performance. The concept of employee resilience is defined as an individual's ability to adapt and recover from stressful or adverse circumstances. In accordance with the conservation of resources theory by Hobfoll (1989), resilient individuals are better equipped to manage stressors, thereby sustaining performance. A positive correlation has been identified between resilience, job satisfaction and enhanced job performance (Cantante-Rodrigues et al., 2021). Digital literacy can be defined as the set of skills, knowledge, and attitudes encompassing the practical and critical utilization, assessment, and creation of information in various digital technologies. The perceived ease of use and perceived usefulness of technology facilitate its acceptance, a process that is further enhanced by digital literacy. A study conducted by Huu (2023) has demonstrated a positive correlation between digital competence and innovative work behaviour, as well as superior job performance.

Collaborative and Organizational Dynamics

It is clear that collaborative behaviours, such as team dynamics and peer influence, and employee social networks, combined with broader organizational factors like leadership style, supervisory assistance, diversity in leadership, change management, organizational culture and organizational transparency, significantly influence performance.

The dynamics of teams and peer influence within an organizational context significantly impact employee performance, primarily through fostering collaboration, trust and effective communication. As postulated by Blau (2017) by the social exchange theory, positive interpersonal interactions between team members result in feelings of value and commitment, leading to enhanced productivity levels. Cohesive team dynamics are of great consequence, as they foster knowledge sharing and mutual support among employees, thereby improving decision-making and job performance (Rahmadani et al., 2020). The presence of trust and minimal interpersonal conflict within teams gives rise to more robust organizational outcomes, indicating that productive peer relationships enhance both individual and collective efficacies in delivering public service. Similarly, Informal employee social networks illustrate the interconnectivity between and across diverse organizational levels, facilitating the exchange of information and collaboration in pursuit of various organizational objectives. This increases resource availability and access, as postulated by the Social Capital Theory put forth by Nahapiet and Ghoshal (1998). Ghani and Malik (2023) discovered that robust employee social networks facilitate collaboration, enhancing job satisfaction and performance.

The leadership style employed exerts a considerable influence on the performance of employees, given that different styles engender divergent

levels of performance. Bass (1985) introduced the concept of transformational leadership, whereby leaders inspire and persuade workers to exceed expectations through their vision and influence. Empirical evidence has demonstrated a positive correlation between this leadership style and enhanced employee performance within the public sector. For instance, a study by Wright et al. (2012) identified a positive relationship between transformational leadership and employee performance, attributing this to increased mission valence and public service motivation. Research has identified that leaders who articulate an appealing vision and demonstrate commitment to public service can enhance employee motivation to perform well (Donkor, 2021; Kawiana et al., 2020; Mahfouz et al., 2020). Consequently, it is incumbent upon organizational leaders to encourage transformational qualities in order to enhance the performance of employees and attain the organization's objectives. Similarly, the degree of supervisory support is a significant factor in determining the quality of the working environment. Supervisory support can be defined as the support and guidance provided by a supervisor to their subordinates. The Leader-Member Exchange (LMX) Theory by Dansereau et al. (1975) posits that the quality of the relationship between supervisors and employees is a significant predictor of communication, trust, and performance. A study by MacIas-Velasquez et al. (2021) revealed a positive correlation between perceived organizational support, including supervisory support, and job satisfaction and performance.

Diversity in leadership entails the presence of leaders from a multitude of backgrounds and perspectives. The Upper Echelons Theory by Hambrick and Mason (1984), posits that the organizational outcomes observed can be attributed to the values and cognitive bases espoused by those occupying the most senior leadership roles. Organizational outcomes

are enhanced when there is diversity in leadership, due to the increased innovation and improved decision-making that this brings about (World Economic Forum, 2023). The field of change management is concerned with the effective implementation of organizational change. This term describes a method of transition or transformation within organizational contexts, specifically in relation to processes, goals, technologies and culture. Lewin (1947) elucidates a three-step process, designated the unfreezing, changing, and refreezing model in nature, which is efficacious in facilitating change. Employee reactions to organizational change are a significant factor influencing subsequent performance (Khaw et al., 2023). It is, therefore, essential to adopt appropriate change management strategies.

Organizational culture is defined as the values, beliefs, and norms that collectively delineate the behavioural expectations of employees within a given organizational context. Schein (2004) described organizational culture as a pattern of shared basic assumptions learned by a group. In the context of the public sector, a positive organizational culture has been found to be associated with increased employee performance. Blom et al. (2020) analyzed the effect of supportive organizational cultures on employee engagement in terms of performance, and the findings indicate that performance is enhanced when the culture promoted by public sector organizations places emphasis on employee well-being and development. Conversely, an unfavourable or excessively rigid organizational culture has frequently been observed to impede performance by hindering creativity and eroding employee morale. This finding emphasizes the pivotal role of organizational culture in determining employee performance. Similarly, the concept of organizational transparency can be defined as the practice of openly sharing the originality of information, decisions, and processes

within an organizational setting. In accordance with the social exchange theory proposed by Blau (2017), the establishment of transparency naturally fosters the growth of trust, thereby encouraging reciprocity between employees and management. A study by Flynn et al. (2024) has demonstrated that increased transparency is associated with enhanced workforce trust and, consequently, superior organizational performance.

Environmental and Structural Factors

The workplace environment, comprising work climate, working environment, physical work environment, organizational structure and clarity, job design and workload, also plays a significant role in employee performance.

The concept of work climate pertains to the perceptions held by employees with regard to their work environment, encompassing elements such as support, recognition, and fairness. According to Schneider and Reichers (1983) seminal definition, work climate is defined as the shared perceptions of organizational policies, practices, and procedures. In the context of the public sector, a positive work climate has been demonstrated to be associated with enhanced employee performance. Awashreh and Alghunaimi (2024) found that a positive work climate, characterized by supportive management, transparency and fairness in policy, will ensure higher levels of employee commitment and engagement, leading to improved performance outcomes. Conversely, a work climate characterized by negativity, such as a dearth of trust or support for employees, has been shown to engender job dissatisfaction and burnout, thereby exerting a detrimental effect on the performance of public servants (Norawati et al., 2024). It can be argued that the relationship between work climate and performance is significant in the public sector, where stability and efficiency are critical factors in effective public service delivery. By

contrast, the working environment can be defined as the social and psychological conditions under which employees perform their duties. Herzberg's Two-Factor Theory (1959) posits that the work environment can be classified as a hygiene factor. While a lack of it may not necessarily lead to increased job satisfaction, it is undoubtedly a significant contributor to job dissatisfaction. A positive work environment is a significant contributor to employee productivity and performance (Faez et al., 2023). This is achieved through the reduction of burnout and the creation of a healthy work atmosphere. The impact of the physical work environment on employee performance, productivity and job satisfaction is also indisputable. Empirical evidence has demonstrated that a meticulously designed workspace, equipped with ergonomic furniture, optimal lighting and temperature settings, has a proven capacity to enhance employee performance. Such environments have been shown to reduce stress and improve comfort, thereby enabling employees to optimize their performance (Basalamah and As'ad, 2021). The provision of adequate physical working conditions has been demonstrated to have a positive effect on job satisfaction, which, in turn, has been shown to contribute to general organizational effectiveness. Consequently, it is imperative to ensure that adequate working conditions are in place to facilitate the creation of an appropriate work environment for staff (Ángeles López-Cabarcos et al., 2022; Chafi et al., 2022).

The presence of clearly defined roles, responsibilities, and hierarchical arrangements is a hallmark of organizational clarity and structure (Weiss, 1983). These concepts are derived from Weber's (1947) bureaucratic theory. The significance of organizational clarity and structure in minimizing ambiguity and maximizing efficiency is well-documented (Johari et al., 2019). Employees are able to understand their roles and work

towards organizational goals when such clarity is in place. A well-established organizational structure has been shown to have a positive impact on various aspects of organizational functioning, including the reduction of role conflict and stress, enhancement of job satisfaction, and improvement in performance (Ancarani et al., 2019). It is, therefore, vital for public service delivery to be improved with clear goals and proper organizational structuring if it is to work efficiently and enhance productivity. In the context of workload and job design, the term "workload" is employed to denote the quantity of work allocated to an individual employee. In contrast, the concept of "job design" encompasses the process of structuring tasks and responsibilities. In their discussion of the Job Demands-Resources Model, Bakker and Demerouti (2007) present the view that high job demands can evoke burnout, whereas fitting job design can facilitate optimal engagement. A well-designed job enhances performance, as the tasks are aligned with the employee's skills and the requisite resources are available (Van den Broeck and Parker, 2017).

Technological and Innovative Factors

The advent of technological and innovative factors has been identified as a key element in this paradigm shift. These factors encompass technological advancement, technological competence and support, integration of technology and work practices, high-performance work systems (HPWS), innovation and creativity and agility and innovation culture.

Technological advancement is defined as the process of integrating new technologies into an organization with the objective of enhancing efficiency and effectiveness. This concept finds resonance with the socio-technical system theory propounded by Trist and Bamforth (1951), which emphasizes the symbiotic relationship between technological development and social structures. The integration of advanced technologies, such as

artificial intelligence and digital technologies, has undeniably precipitated a paradigm shift in employee performance (Zuiderwijk et al., 2021). The integration of advanced technologies within the workplace has been shown to automate routine activities, thereby liberating employees to engage with more critical tasks that demand higher levels of cognitive processing (Asbari et al., 2021). Organizations must implement effective change management and employee training programs that align employee competencies with evolving systems to integrate technology successfully. This is of particular relevance in the context of achieving optimal performance in the public sector (Mensah, 2020).

Concomitantly, the integration of technology into occupational practices entails the incorporation of digital instruments and systems into the quotidian activities of employees, with the objective of enhancing efficiency and productivity. As articulated by the sociotechnical systems theory proposed by Trist and Bamforth (1951), the concurrent optimization of social and technical systems is paramount to attain optimal performance. The digitalization of workplace practices is, therefore, of paramount importance for improving employee engagement and subsequent performance (Nikou et al., 2022). The technology capability of employees is defined as their knowledge and skills in the context of digital technologies and systems. Conversely, technology support encompasses the resources and assistance provided to facilitate their utilization. The Technology Acceptance Model (TAM) by Davis (1989) posits two key factors that are believed to be instrumental in the adoption of technologies: perceived ease of use and perceived usefulness. Marín Díaz et al. (2023) have observed that training programs designed to enhance employees' technological skills positively impact their job performance and organizational efficiency.

High-performance work systems (HPWS) are strategic human resource practices that are designed to enhance organizational effectiveness by fostering employee involvement, commitment, and skills (Mitchell et al., 2013). The resource-based view (RBV) by Wernerfelt (1984), which considers human capital as a source of sustained competitive advantage, provides a theoretical basis for HPWS. These disparate approaches have yielded considerable consequences in the public sector, manifesting HPWS through the assurance of superior performance derived from a motivated, proficient, and devoted workforce (Jatoi et al., 2024). The implementation of HPWS practices, including performance appraisals, training, and employee participation, results in a greater alignment between organizational goals and individual efforts, thereby enhancing performance outcomes (Soomro et al., 2024). Consequently, the strategic integration of human resources management practices in the context of employee performance optimization positions HPWS as a valuable tool in public sector settings. Innovation and creativity are processes concerned with generating and implementing novel ideas and methods within an organizational context. Amabile's Componential Theory of Creativity (1983) posits that intrinsic motivation, in conjunction with a conducive environmental system, is a prerequisite for creativity. The organizational innovation climate has been demonstrated to exert a significant influence on employee innovation potential, as well as to positively impact employee job performance (You et al., 2022). Similarly, an organizational culture that permits agility and innovation encourages adaptability and continuous improvement. To gain insight into the significance of integrating, developing and reconfiguring internal and external competencies in navigating a rapidly evolving environment, one may turn to the Dynamic Capabilities Framework proposed by Teece et al. (1997). Such a culture

enables employees to perform at a higher level, as it encourages creativity and proactive problem-solving (Clauss et al., 2020).

Well-being and Work-Life Integration

The concept of employee well-being, which encompasses employee well-being and mental health, mental health and wellness programs, workplace well-being programs, work-life balance (WLB) and psychological safety, is paramount for maintaining high performance in challenging environments.

Employee Well-being and Mental Health encompass the overall psychological state of employees, recognizing that excessive job demands and insufficient resources can heighten stress and burnout (Bakker and Demerouti, 2007). Providing psychological support and cultivating a positive organizational climate help mitigate these risks and lead to increased job satisfaction and reduced absenteeism (Preston, 2022; Yan et al., 2020). In parallel, Mental Health and Wellness Programs are structured organizational interventions such as stress-management workshops or counseling that specifically target mental health challenges. They reduce detrimental job demands, bolster engagement, and enhance employee performance (Bondar et al., 2022). Workplace Well-being Programs adopt a more holistic approach by addressing employees' physical, psychological, and social needs through various initiatives, from stress management to health promotion. Grounded in the Conservation of Resources Theory, these programs enable employees to conserve and build their personal resources, which lowers burnout rates and boosts productivity (Juba, 2024). Collectively, these three factors underscore how comprehensive support for mental health and well-being benefits not only individual employees but also improves organizational outcomes.

The concept of work-life balance (WLB) can be defined as an individual's capacity to effectively manage the responsibilities associated with their professional and personal lives, thereby minimizing any potential conflict between the two domains. Theory suggests that, according to the role theory proposed Kahn et al. (1964), work-life balance encourages individuals to assume multiple professional and personal roles without experiencing role conflict or strain. WLB has been shown to significantly impact employee performance, with studies indicating that employees who maintain a balanced lifestyle tend to exhibit higher levels of job satisfaction, reduced burnout, and enhanced overall productivity (Preena, 2021). Organizations that offer flexible work arrangements and policies that support work-life balance (WLB) have employees who demonstrate enhanced performance and increased levels of engagement. This phenomenon can be attributed to the positive correlation between effective WLB practices and employee performance (Dousin et al., 2019; Thamrin and Riyanto, 2020). Consequently, WLB is recognized as a pivotal factor in enhancing the efficiency of public sector employees. The concept of psychological safety pertains to the extent to which an individual is willing to take interpersonal risks within a given context, such as in an employment position. This willingness is contingent upon the belief that such risks are not likely to result in adverse consequences. In 1999, Edmondson introduced the phenomenon and asserted that psychological safety facilitates learning and enhanced team performance. A study conducted by Han et al. (2019) revealed a positive association between psychological safety and employee performance and engagement. This is because it facilitates communication and encourages innovation.

Motivation and Recognition Factors

Motivating and recognizing employees is imperative if one wishes to create a high-performing workforce. This will directly influence employee engagement, satisfaction and retention. The key elements of this are compensation, remuneration, employee recognition and reward systems, employee engagement, employee voice and participation, work autonomy and flexibility and remote work capability.

In organizational behaviour, compensation represents a significant motivational factor and is typically directly correlated with the satisfaction-performance paradigm. The remuneration package typically comprises a base salary, supplementary benefits such as healthcare, a pension scheme and job security. These elements are crucial in retaining the services of suitably qualified personnel (Nwosù et al., 2023). The equity theory by Adams (1963) posits that employees evaluate their compensation in relation to others in similar roles. When employees perceive equity, their morale and motivation are enhanced, leading to superior performance (Kackur, 2022). It has been demonstrated through empirical research that transparent and timely compensation plays a pivotal role in fostering occupational satisfaction and commitment among public sector employees, which in turn influences their productivity (AL-Awadhi, 2024). However, issues such as delayed salaries or inadequate compensation can lead to job dissatisfaction, low motivation, and poor performance. Therefore, it is essential to ensure that compensation policies are developed in a way that encourages high employee output (Adea et al., 2024). A well-designed compensation system is crucial for achieving superior performance levels in public entities. Remuneration, which includes monetary compensations such as salaries, bonuses, and incentives, is one of the important motivating factors (Calvin, 2017). This generally emanates from the expectancy theory

by Vroom (1959), which stipulates that if pay is perceived to be fair, then motivation and satisfaction will result. Studies emphasize that a competitive pay structure orients the employee's efforts toward the attainment of organizational objectives, thereby increasing engagement and productivity. For instance, remuneration has been associated with increased job satisfaction and a boost in overall work performance, an indication that meaningful remuneration approaches ensure the performance of a given organization (Alwaki, 2018). On the other hand, well-structured remuneration policies can be associated with job commitment and low turnover rate, bringing forth positive organizational outcomes (Rapsanjani and Johannes, 2019). Remuneration is not the sole factor that determines improved performance. Some employees will remain dissatisfied even with adequate remuneration, which demonstrates that other factors also play a critical role. This proves that employee performance dynamics are more complex than mere financial compensation. Similarly, Employee recognition and reward systems aim to acknowledge and remunerate employees for their contributions and achievements. According to the social exchange theory, as postulated by Blau (2017), such a system serves to enhance reciprocity between employees and the organization, thereby augmenting motivation and performance. A meticulously designed reward system has been shown to exert a positive influence on employee performance, enhancing job satisfaction and mitigating intentions to seek employment elsewhere (Joshi, 2021). Such rewards may include spot bonuses or gift cards, but also praise, career development opportunities and public acknowledgment. These enrich employees' sense of value beyond mere financial compensation. These programs undoubtedly cultivate a supportive work environment characterized by higher job satisfaction and reduced turnover

intentions, highlighting the emotional and relational aspects of employee motivation that traditional pay-centric approaches often overlook.

Employee engagement is a concept derived from organizational psychology. It can be defined as the emotional commitment of employees to their roles and organizations (Khan, 2024). The Job Demands-Resources (JD-R) model by Bakker and Demerouti (2007) suggests that engaged employees are more proactive and contribute positively to high performance. This is because such employees are motivated by supportive resources and manageable demands. This is particularly relevant in the public sector, where engagement can serve as the foundation for efficiency and quality in the delivery of public services (Garba et al., 2024). Many research studies have indicated that employees are most engaged when they perceive supportive leadership and recognition, opportunities for professional growth, and productivity increases, leading to positive organizational outcomes (Zawolo et al., 2024). However, a lack of engagement leads to burnout, reduced job satisfaction and high turnover rates, negatively impacting performance in institutions (Awashreh and Alghunaimi, 2024). Therefore, at an organizational culture level, engagement is instrumental in maintaining and continuously improving performance in public sector organizations. Similarly, employee voice is used to describe the opportunities afforded to employees to express their opinions and exert influence over organizational decisions. In the context of the participation theory, Pateman (1970) posits that the degree of involvement in decision-making processes is positively correlated with levels of commitment and performance. A study undertaken in public sector organizations by Alang et al. (2022) established that inclusive leadership behaviours facilitated workplace diversity through support for the presence and development of underrepresented groups, thereby

amplifying employee voice and perception of inclusion. This inclusive approach will engender a more engaged and higher-performing workforce, as workers will be more connected to and committed to the organizational goals.

Work autonomy and flexibility are also identified as key motivational factors. Work autonomy can be defined as the degree of control that employees have over their activities and planning issues. The self-determination theory by Deci and Ryan (1985) posits that autonomy is one of three fundamental psychological needs, along with competence and relatedness, which serve to enhance intrinsic motivational processes. The provision of flexible work arrangements has been demonstrated to enhance employee productivity and improve the performance of human resources functions (Turner, 2023). The relevance of flexible work arrangements, such as capabilities, has increased significantly in the context of hybrid work models. This term refers to an organization's capacity to facilitate the work of employees based outside of the traditional office environment. The JD-R model posits that the availability of remote work and other resources has a positive impact on employee well-being and performance. A study was undertaken by Wang et al. (2021) indicated that flexibility in remote work is associated with enhanced productivity and job satisfaction.

Development and Growth Opportunities

The development and growth opportunities facilitate continuous improvement and adaptability through professional and personal growth. Investment in employee development is an effective means of enhancing organizational productivity and individual competence. These elements can encompass various aspects, including training and development opportunities, crisis management training, personal development opportunities, mentoring and coaching and feedback culture.

Training and development are essential for improving employees' skills, knowledge and competencies, directly impacting their performance. The Human Capital Theory developed by Becker (2010) emphasizes investments in the development of employees because this will enhance productivity within an organization. Organized training programs are highly effective in strengthening service delivery and improving employee efficiency (Iis et al., 2022). When employees feel that there are enough development opportunities, they are more motivated and satisfied, which brings more remarkable performance outcomes (Davidescu et al., 2020). Therefore, continuous learning initiatives are key to driving innovation and adaptability in the face of emerging public service demands. Crisis management training enhances employees' capacity to respond efficiently during emergencies or unforeseen circumstances. As Coombs (2007) posits, the situational crisis communication Theory (SCCT) proposes that implementing appropriate training can mitigate the adverse consequences of crises. Alariki and Al-Abed (2021) posit that organizations with comprehensive crisis management training programs demonstrate enhanced employee performance during crises, attributable to augmented preparedness and confidence.

Personal development opportunities are used to describe programs designed to facilitate the enhancement of employees' skills and competencies. The Self-Determination Theory, as Deci and Ryan (1985) put forth, suggests that intrinsic motivation through personal growth is a key driver of enhanced performance. A study by Zervas and Stiakakis (2024) posits that HR leadership in facilitating digital skills acquisition significantly contributes to sustainable economic development and employee performance. Mentoring and coaching initiatives are recognized as pivotal developmental tools that enhance employees' skills and career

progression. The process entails the provision of guidance and support, with the objective of facilitating the enhancement and advancement of employees' competencies and their professional trajectory. Following Social Learning Theory, by Bandura (1977) it was established that the learning process occurs due to observation and interaction. In organizational contexts, coaching has been demonstrated to enhance performance, particularly concerning goal attainment and self-efficacy (Wang et al., 2022). Similarly, the feedback culture is used to describe an organizational setting that values and encourages the provision of frequent, constructive feedback. The feedback intervention theory (FIT), as proposed by Kluger and DeNisi (1996), posits that feedback has the capacity to influence both behaviour and performance. Recent empirical studies have identified that timely, specific, and constructive feedback, besides clarifying expectations, leads to better employee engagement and performance. By consistently communicating strengths and developmental areas, organizations enable employees to adjust their behaviours and improve task performance more rapidly (Evans and Dobrosielska, 2021). Consequently, the cultivation of a comprehensive feedback environment has the potential to contribute to enhanced productivity, job satisfaction, and overall organizational effectiveness among employees.

Diversity and Sustainable Practices

In today’s business world, there is a growing focus on the importance of diversity, sustainability, and ethical practices as essential parts of organizational frameworks. These aspects play a crucial role in shaping how organizations operate and their ability to create a supportive, inclusive culture for their employees. They cover a broad spectrum, from workplace diversity and inclusion and inclusion beyond diversity to sustainability and ethical practices and environmental sustainability initiatives.

Diversity and inclusion in the workplace refer to the presence of differences within a given setting and the practice of ensuring that all individuals feel valued and respected, respectively. The Social Identity Theory by Tajfel (1979) posits that individuals derive part of their identity from the memberships they possess within groups, which again influences their behaviours and attitudes at work. Indeed, the results of the meta-analysis by Holmes et al. (2021) demonstrate the positive effect of a positive diversity climate on employees' attitudes and performance. Similarly, inclusion beyond diversity is a broader concept than diversity, which is concerned with creating an environment conducive to the inclusion and valuing of all individuals. As Allport (1954) the contact hypothesis posits that interpersonal contact is an efficacious method for reducing prejudice between majority and minority group members, contingent on the circumstances. Implementing inclusionary practices has enhanced engagement and improved performance, fostering a sense of belonging (Li et al., 2024).

Business conduct must be socially responsible and environmentally sustainable. The Triple Bottom Line framework proposed by Elkington (1998) clearly shows how economic, social and environmental concerns must be balanced. There is a positive correlation between corporate social responsibility and employee commitment and performance, as a study by Pham and Kim (2019) definitively found. The Triple Bottom Line framework aims to achieve a state of equilibrium between economic, social, and ecological concerns. A study by Ahsan and Khawaja (2024) posits that sustainable leadership positively influences environmental performance, which is mediated by employee well-being and innovation.

The factors influencing employee performance can be summarized as presented in Table 2.2.

Table 2.2: Summary of factors affecting employee performance discovered from SLR

	Factor	Theoretical Basis	Key References	Impact on Performance
1	Public Service Motivation (PSM)	Seminal Framework Developed by Perry and Wise (1990)	Sudha et al. (2023), Zhang (2023)	Increased job satisfaction and improved job performance
2	Job Satisfaction	Herzberg's Two-Factor Theory (1959)	Min et al. (2021)	Higher productivity and alignment with organizational goals
3	Organizational Commitment	Meyer and Allen's Three-Component Model (1991)	Harahap et al. (2024), Ying et al. (2024)	Enhanced productivity, lower turnover rates
4	Proactive Behaviour	Proactive personality by Bateman and Crant (1993)	Wang et al. (2024)	Improved job satisfaction and performance
5	Organizational Citizenship Behaviours (OCBs)	OCB by Organ (1988)	Widayati et al. (2020), Bustomi et al. (2020)	Positive contribution to organizational functioning
6	Employee Autonomy	Hackman and Oldham's Job Characteristics Model (1976)	Ciobanu et al. (2019)	Motivated employees and increased job satisfaction
7	Emotional Intelligence (EI)	Daniel Goleman (1995)'s emotional intelligence theory	Zampetakis and Mitropoulou (2024)	Stronger relationships and stress management
8	Communication Skills	Communication model by Burks et al. (1951)	Gbarale and Lebura (2020)	Enhanced transparency and cooperation
9	Knowledge-Sharing Ability	Social Exchange Theory by Blau (2017)	Kim et al. (2024), Nguyen et al. (2020)	Promotes collaboration and innovation
10	Cognitive Abilities	Spearman's g-factor (1904)	Nye et al. (2022)	Efficient execution of complex tasks
11	Competence	Competency theory by Boyatzis (1982)	Yulius (2021)	Critical for service delivery and quality outcomes
12	Adaptability	Individual adaptability (I-ADAPT) theory by Ployhart and Bliese (2006)	Park and Park (2020)	Better coping strategies and superior performance

	Factor	Theoretical Basis	Key References	Impact on Performance
13	Employee Resilience	Conservation of Resources Theory by Hobfoll (1989)	Cantante-Rodrigues et al. (2021)	Sustains performance under stress
14	Digital Literacy and Skills	Technology Acceptance Model by Davis (1989)	Huu (2023)	Enables innovative work behaviour
15	Team Dynamics and Peer Influene	Social Exchange Theory by Blau (2017)	Rahmadani et al. (2020)	Improved collaboration and decision-making
16	Employee Social Networks	Social Capital Theory by Nahapiet and Ghoshal (1998)	Ghani and Malik (2023)	Enhances collaboration and access to resources
17	Leadership Style	Transformational Leadership by Bass (1985)	Wright et al. (2012), Kawiana et al. (2020)	Enhanced motivation and public service outcomes
18	Supervisory Assistance	Leader-Member Exchange (LMX) Theory by Dansereau et al. (1975)	MacIas-Velasquez et al. (2021)	Increased trust and performance
19	Diversity in Leadership	Upper Echelons Theory by Hambrick and Mason (1984)	World Economic Forum (2023)	Improved decision-making and innovation
20	Change Management	Lewin's Change Model (1947)	Khaw et al. (2023)	Facilitates effective organizational transitions
21	Organizational Culture	Schein’s iceberg model (1992)	Blom et al. (2020)	Enhances engagement and creativity
22	Organizational Transparency	Social Exchange Theory by Blau (2017)	Flynn et al. (2024)	Builds trust and improves performance
23	Work Climate	Schneider and Reichers (1983)	Awashreh and Alghunaimi (2024)	Promotes engagement and reduces burnout
24	Working Environment	Herzberg's Two-Factor Theory (1959)	Faez et al. (2023)	Contributes to productivity and job satisfaction

	Factor	Theoretical Basis	Key References	Impact on Performance
25	Physical Work Environment	Job Demands-Resources Model by Bakker and Demerouti (2007)	Basalamah and As'ad (2021), Ángeles López-Cabarcos et al. (2022), Chafi et al. (2022)	Enhances comfort and reduces stress
26	Organizational Structure and Clarity	Weber's Bureaucratic Theory (1947)	Johari et al. (2019)	Reduces ambiguity and role conflict
27	Job Design and Workload	Job Demands-Resources Model by Bakker and Demerouti (2007)	Van den Broeck and Parker (2017)	Enhances engagement and reduces burnout
28	Technological Advancement	Socio-technical System Theory by Trist and Bamforth (1951)	Zuiderwijk et al. (2021)	Automates routine tasks, freeing up cognitive resources
29	Technological Competence and Support	Technology Acceptance Model (TAM) by Davis (1989)	Marín Díaz et al. (2023)	Enhances employees' technological skills positively
30	Integration of Technology and Work Practices	Socio-technical system theory propounded by Trist and Bamforth (1951)	Nikou et al. (2022)	Aiming to improve efficiency and productivity
31	High-Performance Work Systems (HPWS)	Resource-Based View (RBV) by Wernerfelt (1984)	Jatoi et al. (2024), Soomro et al. (2024)	Aligns organizational goals with individual efforts
32	Innovation and Creativity	Componential Theory of Creativity by Amabile (1983)	You et al. (2022)	Encourages problem-solving and higher performance
33	Agility and Innovation Culture	Dynamic capabilities framework proposed by Teece et al. (1997)	Clauss et al. (2020)	encourages creativity and proactive problem-solving
34	employee well-being and mental health	Conservation of Resources Theory by Hobfoll (1989)	Preston (2022), Yan et al. (2020)	Reduces absenteeism and increases job satisfaction
35	Mental Health and Wellness Programs	Job Demands-Resources Model by Bakker and Demerouti (2007)	Bondar et al. (2022)	Enhances employee well-being and performance

	Factor	Theoretical Basis	Key References	Impact on Performance
36	Workplace Well-being Programs	Conservation of Resources Theory by Hobfoll (1989)	Juba (2024)	Engaged, productive and committed to organizational goals.
37	Work-Life Balance (WLB)	Role Theory by Kahn et al. (1964)	Preena (2021), Dousin et al. (2019)	Improves productivity and reduces burnout
38	Psychological Safety	Edmondson's theory of psychological safety (1990)	Han et al. (2019)	Encourages innovation and communication
39	Compensation	Equity theory by Adams (1963)	Kackur (2022), AL-Awadhi (2024), Adea et al. (2024)	Fosters occupational satisfaction and commitment
40	Remuneration	Expectancy theory by Vroom (1959)	Alwaki (2018), Rapsanjani and Johannes (2019)	associated with job commitment and a low turnover rate
41	Employee Recognition and Reward Systems	Social Exchange Theory by Blau (2017)	Joshi (2021)	Enhances motivation and job satisfaction
42	Employee Engagement	Job Demands-Resources Model by Bakker and Demerouti (2007)	Zawolo et al. (2024)	Boosts efficiency and quality
43	Employee Voice and Participation	Participation Theory by Pateman (1970)	Alang et al. (2022)	Enhances commitment and inclusion
44	Work Autonomy and Flexibility	Self-determination theory by Deci and Ryan (1985)	Turner (2023)	enhance employee productivity and improve HR functions
45	Remote Work Capability	Job Demands-Resources Model by Bakker and Demerouti (2007)	Wang et al. (2021)	associated with enhanced productivity and job satisfaction
46	Training and Development Opportunities	Human Capital Theory by Becker (2010)	Iis et al. (2022)	Improves efficiency and service delivery
47	Crisis Management Training	Situational Crisis Communication Theory by Coombs (2007)	Alariki and Al-Abed (2021)	Enhances preparedness and performance

	Factor	Theoretical Basis	Key References	Impact on Performance
48	Personal Development Opportunities	Self-Determination Theory by Deci and Ryan (1985)	Zervas and Stiakakis (2024)	contributes to sustainable economic development
49	Mentoring and Coaching	Social Learning Theory by Bandura (1977)	Wang et al. (2022)	Improves competencies and goal attainment
50	Feedback Culture	Feedback Intervention Theory (FIT) by Kluger and DeNisi (1996)	Evans and Dobrosielska (2021)	Improves engagement and task performance
51	Workplace Diversity and Inclusion	Social Identity Theory by Tajfel (1979)	Holmes et al. (2021)	Improves attitudes and performance
52	Inclusion Beyond Diversity	Contact Hypothesis by Allport (1954)	Li et al. (2024)	It enhances engagement and fosters a sense of belonging
53	Sustainability and Ethical Practices	Triple Bottom Line Framework by Elkington (1998)	Pham and Kim (2019)	Balances social, economic, and ecological goals
54	Environmental Sustainability Initiatives	Triple Bottom Line Framework by Elkington (1998)	Ahsan and Khawaja (2024)	Exert a positive influence on environmental performance

It is important to acknowledge the complexity of these factors, which often renders it unfeasible to capture the full breadth of factors that shape organizational outcomes (Robbins and Judge, 2022). These influences encompass personal attributes, such as individual skill sets, motivation, psychological dispositions, and broader organizational features, including leadership approaches and the prevailing organizational culture (Schein, 2016; Yukl, 2013). Externally, environmental conditions, such as economic pressures and political climates, further complicate this complexity by creating constantly shifting contexts. Consequently, the adaptability of any overarching strategy is contingent on the distinct characteristics of various organizations, industries, and geographic regions. The subjective nature of constructs such as job satisfaction and psychological well-being, which vary considerably from one person to another (Diener, 2000), adds to the challenge.

This dynamism is further exacerbated by ongoing technological developments, particularly the spread of artificial intelligence and the rise of remote work, which continuously reshape the workplace (Brynjolfsson and Mcafee, 2016). Furthermore, employees often respond to identical stimuli in distinct ways, emphasizing the significance of individual differences in mediating the influence of these factors on performance (Robbins and Judge, 2022). As research in cognitive science continues to reveal additional factors that influence workplace effectiveness, creating a comprehensive catalogue of all potential factors becomes increasingly impractical. Consequently, the primary focus in this study is on the most influential and commonly observed elements rather than on an all-encompassing inventory in order to reflect prevailing trends without assuming comprehensiveness.

2.2.3 Employee Performance in the Bahraini Public Sector: A Contextual Review

While the preceding review highlights a broad spectrum of factors influencing employee performance across diverse international settings, it is essential to recognize the impact of specific cultural, institutional, and policy environments. In the Kingdom of Bahrain, national strategies such as Vision 2030 and ongoing civil service reforms may intersect with these globally identified performance drivers in ways that diverge from or amplify established patterns (Bahrain Economic Development Board, 2021). Moreover, local socio-cultural norms, governance structures, and economic priorities can shape how motivational factors, leadership approaches, and technological innovations are implemented and perceived in the public sector (Budhwar and Mellahi, 2016). Hence, to fully appreciate the nuances of performance management within Bahraini governmental organizations, this section contextualizes these global insights by examining existing regional and national research, highlighting areas where additional empirical inquiry is both necessary and timely.

The Kingdom of Bahrain, a small island nation in the Arabian Gulf, has long been distinguished by its relatively open economy and distinct model of public administration. Among Gulf Cooperation Council (GCC) states, Bahrain is notable for its bicameral legislature, which includes an elected assembly. This arrangement has the capacity to influence policy formulation and public-sector governance in ways that differ from those of neighbouring countries (Common, 2008). Despite the emergence of social and political tensions, the Bahraini public sector has demonstrated a consistent commitment to prioritizing citizen-centric services by allocating resources to industries such as education, healthcare, housing, and social welfare. A significant catalyst for these reforms has been the digital transformation, particularly e-government initiatives, which have

enhanced the efficiency, transparency, and accessibility of public services (Mahmood et al., 2019).

Since the early 2000s, Bahrain has pursued an intensive reform agenda aimed at diversifying its economic base away from oil and gas revenues. Key national frameworks, such as Vision 2030, emphasize sustainable development, entrepreneurship, and enhanced public-service delivery. However, as with other GCC nations, there is a paucity of empirical research in the form of publications in high-impact international journals on the management of the public sector (Biygautane, 2023a). Nonetheless, World Bank data on government effectiveness from 2010 to 2024 show significant progress in addressing pressing challenges, including human development, environmental performance, and the expansion of online government services. Bahrain's advancement in these areas has resulted in its favourable positioning in the IMD Global Competitiveness Report (2024), where it attained eighth place in the adaptability of government policies to change, sixth in facilitating public-private collaboration in technology, and ninth in the efficiency of financial and banking services.

Furthermore, Bahrain's commitment to trade and investment liberalization is evidenced by its consistent ranking at the forefront within the MENA region, as reported by The Heritage Foundation's Economic Freedom Index (2024). Bahrain's leadership in Islamic finance and its emphasis on youth empowerment reflect a sustained focus on human capital development, as evidenced by its attainment of fourth place globally in terms of skilled labour availability and sixth place for technological, digital, and financial competencies. These advancements extend to the logistics sector, with the country rising to 25th in the DHL Global Connectivity Index (2024). Such achievements have helped cultivate a positive public-sector environment, where improvements in

infrastructure, digitization, and national competitiveness foster higher levels of employee engagement and a sense of professional growth.

Surveys of Bahraini civil servants further underscore this supportive organizational climate. A global HR consulting study in 2010 revealed that 93% of Bahrain's public-sector employees reported medium-to-high career orientation, 92% felt pride in their institutions, and overall employee engagement stood at around 85% (Elliott et al., 2024). These figures suggest that governmental reforms, combined with a culture of excellence, have made skill enhancement and professional development core tenets of Bahrain's civil service ethos. Over time, this culture of achievement has yielded new opportunities for recognition and career progression, reinforcing positive perceptions of the public sector among employees.

Several private-sector studies in Bahrain offer insights into the factors shaping employee performance, albeit outside the public domain. For instance, Albaqqali and Sankar (2019) definitively identified a strong correlation between employee empowerment and job performance in local banks, citing the significance of delegation of authority, teamwork, participation, and communication. In accounting firms, Banta and Shaikh (2017) concluded that compensation and benefits are crucial in improving job performance, while Urubio (2017) emphasized the impact of financial and non-financial incentives on employee outcomes in select Bahraini companies. Bader and Sankar (2019) demonstrated that attendance management has a measurable influence on staff performance in Bahraini banks, and Alaradi and Sankar (2019) confirmed a positive association between certain human resource management practices and higher performance levels among employees of small and medium-sized enterprises. While these findings emphasize the importance of empowerment, compensation, and HR policies, they predominantly

represent private-sector perspectives, leaving the nature and extent of such factors in the public sector relatively underexplored.

In contrast, the number of research activities dealing straightforwardly with Bahrain's public sector is low and generally touches narrow or highly specialized issues. For instance, Shamlooh and Doblas (2020) examined the effects of ISO 9001:2015 on employee performance in the Ministry of Industry, Commerce and Tourism. They found that management commitment, internal communication, and workplace environment played the most significant roles. Hassan and Aljawder (2020) focused on performance appraisal efficiency in government offices. They identified several issues, including a lack of managerial awareness, non-compliance with the law, outdated procedures, and reliance on obsolete performance documentation. They recommended digitalizing the performance evaluation system, incorporating 360-degree evaluation, and, in the future, including AI to reduce biased opinions. Abu Shanab et al. (2021) examined the appraisal system in conjunction with the COVID-19 pandemic. They stressed that ongoing communication, rewards corresponding to the fact, and remote-friendly policies are crucial for employee engagement. AlBanki and Badawi (2019) investigated job enrichment in the public sector. They concluded that increased responsibility and opportunities for growth substantially enhance employees' satisfaction, while job independence has a comparatively weaker effect.

Beyond these core studies, a handful of regional and GCC-focused publications also contextualize performance management challenges relevant to Bahrain. Budhwar and Mellahi (2016), in their Handbook of Human Resource Management in the Middle East, state that public-sector HR in several Gulf countries (including Bahrain) is marked by high centralization and bureaucracy, potentially constraining employee

autonomy and innovation. Al-Alawi et al. (2007) explored knowledge sharing in a Bahraini organizational context, showing that supportive leadership and a conducive organizational culture significantly affect information exchange and, by extension, performance outcomes. Biygautane (2023) has also addressed HRM reform in the GCC, highlighting the challenges of modernizing public institutions while maintaining local cultural values. These findings point to broader themes, centralized governance, cultural norms, and technology adoption, that inevitably influence how performance management practices unfold in Bahrain's government agencies.

While such contributions are beneficial, empirical research employing advanced or predictive methods in the Bahraini public sector remains limited. Studies exploring performance appraisal systems and quality management initiatives are valuable but do not encompass the full range of well-established global performance drivers, particularly those associated with autonomy, emotional intelligence, and AI-based HR frameworks. Furthermore, most public sector studies rely on cross-sectional or qualitative designs, which makes it challenging to capture evolving trends or to predict long-term performance outcomes. Limited empirical evidence describes how AI-driven tools could streamline employee evaluations, enhance data-informed decisions, or reduce human biases in recruitment and appraisal processes.

These limitations underscore a major gap in literature. Although certain factors influencing employee performance, such as management commitment, communication, appraisal effectiveness, and job enrichment, have been identified, no comprehensive framework unifies these drivers into a predictive, AI-enabled model specifically designed for the public sector. Addressing this gap could provide tangible benefits for

policymakers and practitioners, particularly as Bahrain continues to pursue digital transformation and align its public services with national and international benchmarks. Therefore, future research in this field holds the potential to bridge theoretical insights from global HR scholarship with practical innovations that correspond to Bahrain's evolving governmental priorities.

The studies reviewed thus far highlight the pivotal role of institutional culture, appraisal systems, and managerial commitment in shaping employee performance outcomes within Bahrain's public sector. While these findings underscore important contextual nuances, such as the tendency toward centralized decision-making and the emerging emphasis on digital transformation, existing scholarship seldom employs advanced or predictive methods to manage and forecast employee performance. Indeed, several authors, including Hassan and Aljawder (2020), have recommended exploring artificial intelligence (AI) as a means of minimizing bias and enhancing the effectiveness of performance evaluations. Yet, no comprehensive framework has emerged in which global theories of employee performance are integrated with AI-driven tools specifically tailored for Bahrain's governmental landscape.

Against this backdrop, the following section examines the intersection of AI technologies and performance management, drawing on international research to identify how predictive analytics and machine learning are reshaping HR practices worldwide. This exploration will lay the groundwork for identifying additional gaps, particularly regarding how Bahrain's public sector could harness AI to bolster employee engagement, productivity, and strategic decision-making. Synthesizing global AI innovations with local reform imperatives can better delineate the path forward for data-driven performance management in the Kingdom.

2.3 From Traditional to AI-Based Approaches

Artificial intelligence (AI) has evolved to encompass the development of computational systems designed to execute tasks that typically require human-level intelligence, such as perception, decision-making, and learning (Jordan and Mitchell, 2015; LeCun et al., 2015). Early conceptions of AI framed the field as endeavouring to replicate or exceed cognitive functioning using symbolic reasoning, pattern recognition, and adaptive algorithms (Nilsson, 2009). However, recent breakthroughs in machine learning, deep learning, have precipitated a paradigm shift in this domain, mainly attributable to enhanced computational capabilities and the availability of voluminous datasets (Jordan and Mitchell, 2015). Researchers, as evidenced by LeCun et al. (2015) and Silver et al. (2017), have demonstrated that AI can independently acquire complex tasks. These findings emphasize the extent to which algorithmic innovations can attain performance levels that are difficult or impossible for a human expert to achieve. Accordingly, this has established AI as one of the cornerstones of modern computing, with applications ranging from speech recognition, language modelling, and robotics to predictive analytics.

Building on these foundational advances, AI now permeates everyday life through technologies such as smartphone voice assistants and autonomous vehicles (Russell and Norvig, 2020). At the theoretical level, AI research is anchored by a wide range of methods, including deep learning for pattern recognition, natural language processing for handling human speech, and expert systems that codify specialized knowledge (Kühl et al., 2022). While the origins of AI extend as far back as the mid-20th century (Cao, 2017), it is in the past two decades that its development has undergone an unparalleled acceleration, catalyzed by deep learning

architectures that enable increasingly sophisticated pattern recognition (Chang et al., 2019).

From a pragmatic standpoint, artificial intelligence has been demonstrated to possess a high degree of versatility across a variety of industries, including but not limited to health, finance and education. Examples of its applications include monitoring the depth of anaesthesia in surgeries (Hashimoto et al., 2020) and the optimization of inventory flows and patient scheduling (Abhinav and Naga Subrahmanyam, 2019). These illustrations demonstrate the potential of AI to bring about transformative changes in operational processes. In education, Massive Open Online Courses (MOOCs) leverage AI to enhance teaching and manage courses, facilitating seamless learning processes (Li, 2019). In industry, many aspects of human labour have been combined with sophisticated artificial intelligence systems and have thus been proven to enhance automation and increase productivity (Veselovsky et al., 2021). The finance and accounting sector has experienced notable progress in efficiency, with the integration of AI resulting in the generation of high-quality outputs with reduced errors (Askary et al., 2018; Haseski, 2019). The role of AI in human resources management, encompassing automated decision-making and the handling of repetitive tasks, has been demonstrated to have a substantial business impact on day-to-day operations (Chulanova, 2020).

However, it is important to acknowledge the significant drawbacks and ethical considerations associated with the use of artificial intelligence. Of primary concern is the issue of algorithmic bias, which occurs when flawed and unrepresentative training data results in model outcomes that are discriminatory (Suresh and Guttag, 2021). These issues become most evident in contexts where the outcomes of decision-making processes are

of paramount importance, such as in healthcare settings where stringent privacy measures must be strictly enforced (Spector-Bagdady et al., 2022). Similarly, in the legal field, the demand for transparent and accountable algorithms continues to be a significant concern (Scherer, 2019). Tackling these risks requires collaboration across disciplines, involving computer scientists, legal experts, and ethicists, to ensure that AI develops in line with societal needs and values.

Consequently, as AI matures from its research laboratory roots to a technology with broad commercial and public-sector impact, it promises to revolutionize multiple industries and improve well-being across societies. The ensuing sections explore the intersection of these advancements with employee performance management, delineating the practical applications and theoretical underpinnings of AI in shaping human resource strategies. This subject matter assumes particular pertinence in regions undergoing extensive digital transformation, a salient example being the Kingdom of Bahrain.

2.3.1 AI-Enabled Predictive Models in Employee Performance Management

The ability to make predictions of events or future trends has long been integral to decision-making across a diverse range of fields, including economics, engineering and epidemiology. Historically, early predictive models relied on classic statistical approaches, with regression and time-series analysis being notable examples (Box et al., 2008). As the availability of large datasets has increased over time, the scope of predictive methods has expanded to encompass complex pattern detection and emergent risk forecasting by developing sophisticated machine learning techniques (Breiman, 2001; Jordan and Mitchell, 2015). While many modern algorithms exist, many traditional statistical methodologies

remain highly relevant, especially when interpretability or transparency is paramount. The capacity to predict has rendered human resource management a highly prized aspect, with the potential to pre-empt challenges to the workforce, including personnel turnover, skills gaps and performance variability. This, in turn, enables the implementation of recruitment, training and retention strategies (Stone and Deadrick, 2015). This predictive orientation supports more efficient resource allocation, higher levels of employee satisfaction, and the mitigation of operational uncertainties. Consequently, prediction has emerged as a pivotal conduit between raw data and actionable intelligence, facilitating data-driven decision-making across diverse organizational domains.

Predictive analytics can be defined as a narrow branch of a broader predictive concept, wherein machine learning, statistical methods and expertise in the area are merged to forecast events or behaviours using historical data (Shmueli, 2010). In contradistinction to descriptive analytics, which is concerned with explaining past events, predictive analytics aims to provide highly accurate predictions, typically utilizing substantial datasets combined with sophisticated algorithms to discern subtle trends (Siegel, 2013). These capabilities offer human resource management unique insight into the potential vulnerabilities of the workforce, such as impending attrition or periods of reduced productivity, and enable better-informed decisions regarding recruitment, employee development, and performance interventions (Waller and Fawcett, 2013). These predictive insights collectively form the conceptual backbone of predictive models, in which statistical rigour and algorithmic sophistication combine forces to translate forecasts into scalable real-world applications.

Predictive models are becoming popular in various fields to analyze historical data patterns using statistical or machine learning algorithms. Z. Wang and Srinivasan (2017) describe that this method generates meaningful insights and improves overall accuracy and efficiency in predicting future events or outcomes. In fact, such techniques have shown promise in human resource management, particularly in optimizing employee performance. Predictive models based on artificial intelligence and machine learning methods could revolutionize performance management by enabling companies to make more informed decisions based on relevant insights and gain a deeper understanding of workforce dynamics. For Kapoor and Sherif (2012), predictive models represent significant opportunities to improve employee performance as they can leverage business intelligence (BI) and data analytics technologies in the design of HR database strategies while serving as a precursor to adopting HR management protocols. Applying predictive models allows organizations to analyze employee performance data and identify patterns and trends that can serve as the basis for targeted interventions. This is particularly important for banks as there is a direct correlation between employee performance and organizational success (López and González, 2020).

Predictive models also help management to accurately identify employees' psychological needs to provide tailored incentives that trigger higher levels of motivation and job satisfaction (DiClaudio, 2019). Furthermore, forecasting job participation rates using predictive model algorithms such as Support Vector Machines or Neural Networks makes retention planning more seamless (Choi and Choi, 2020). The role of AI-based predictive models in improving employee performance management effectiveness seems promising. The technology mainly involves predicting

work efficiency by analyzing factors such as demographic information alongside previous work performance records (Sánchez et al., 2022). Such information forms a basis for effective human resource management practices, which include objective goal-setting approaches, performance appraisal systems, and targeted career development initiatives. By using artificial intelligence-based technology for predictive models, companies gain a unique perspective on the complex drivers of work outcomes, such as engagement levels or overall job satisfaction rates. Armed with this knowledge, companies can take timely actions that increase organizational productivity by, among other things, refining leadership approaches and incentivizing the development of workplace competencies. Early identification of high-risk individuals who are prone to underperforming or attrition is also instrumental in keeping teams focused and motivated (Gutiérrez et al., 2022).

2.3.2 Integrating Machine Learning into Employee Performance Management

In the context of data-driven decision-making, conventional systems predominantly depend on leadership guided by subjective judgement and constrained by limited data inputs. In contrast, contemporary models encompass leadership behaviours and employee engagement within team dynamics, underscoring the multifaceted nature of performance. However, contemporary EPM frameworks encounter two common challenges. Firstly, there is a need for precise, prompt forecasts of employee performance, compounded by the evolution of work structures and roles towards greater flexibility. Secondly, voluminous, high-dimensional data sets that encompass numerous dimensions of behavioural variability among employees and organizational contextual variability are involved. These necessitate progressively sophisticated techniques for the accurate measurement and forecasting of performance. In this context, machine

learning emerges as a pivotal technique, especially when combined with robust feature selection, to enhance the accuracy of performance predictions.

Indeed, there has been a growth trend towards using machine learning algorithms to deal with the complexity of EPM. A range of studies conducted within the domain of EPM has incorporated an array of machine learning (ML) models, including conventional methods like Decision Trees, Random Forest, and Logistic Regression, and state-of-the-art techniques, including Gradient Boosting, XGBoost, SVM, Artificial Neural Networks, and ensembles (Fallucchi et al., 2020; Manyika et al., 2021). Integrating these models enables the consideration of individual, team, and organizational factors, thereby enhancing the accuracy of performance predictions and facilitating proactive action.

One of the most recent works was a study by Alsubaie and Aldoukhi (2024), who developed machine learning models to predict employee attrition using IBM datasets available on Kaggle. The dataset contained 1,470 employees and 35 attributes related to factors affecting attrition. The authors used Decision Tree, Random Forest, and Binary Logistic Regression models, applying stepwise regression for the feature selection process and various statistical techniques to improve them. They also determined the most essential variables to predict employee attrition. According to their results, Logistic regression achieved the highest prediction accuracy of 87.44%. Similarly, Ahmed et al. (2023) carried out a study examining the use of machine learning algorithms to forecast employee performance in administrative roles systems. Two datasets were utilized in this study. The first dataset, the Employee Attrition dataset from Kaggle, contains 1200 records of simulated employee attrition and performance information. The second dataset, employee performance data

from the Kenya School of Government database, comprises 206 actual records of employee performance appraisal. The paper used the first dataset to explore the factors affecting employee attrition and the second dataset to predict employee performance through machine learning models. The authors did not specify which feature selection techniques they used, but they employed dimensionality reduction techniques to reduce the number of features and select the most pertinent ones. They compared the accuracy, precision, and recall of five machine learning algorithms F1-score, including KNN, Decision Tree, SVM, Gradient Boosting, and C4.5. The study revealed that SVM attained the greatest accuracy at 98%. The authors suggested that machine learning could provide managers with practical advice to improve individual performance. Another study by Jafor et al. (2023) showed that machine learning can predict employee promotion accurately, a crucial aspect of human resource management. The study used an imbalanced dataset of 54,808 employees from Kaggle, balanced using the SMOTE technique. The authors employed feature engineering techniques like Feature Analysis Tool (FAT) to scrutinize the factors which were the main things of employee promotion and major and minor feature extracting techniques to extract key features such as innovation, experience, punctuality, managerial ability. The machine learning techniques were evaluated, including SVM, Artificial Neural Network, Logistic Regression, XGBoost, Random Forest, and AdaBoost, according to their accuracy, precision, recall, and F1-score. The study proposed a modified AdaBoost approach, using an Artificial Neural Network as the base classifier instead of the standard decision tree. The proposed method outperformed all other techniques with an accuracy of 95.30%.

Razali et al. (2023) developed machine learning models for predicting employee productivity in an academic institution in Sarawak, Malaysia,

using data from 103 employees. They employed several algorithms to rank the attributes that had a significant impact on productivity, such as Info Gain Attribute Eval, Gain Ratio Attribute Eval, Correlation Attribute Eval, One R Attribute Eval, and Relief F. The study found that the linear regression model achieved the best performance regarding Mean Absolute Error (MAE) and Mean Squared Error (MSE), with values of 0.4878 and 0.4682, respectively and identified that department, actual productive hours, and internet speed were highly influential factors. The authors used data visualization techniques to provide valuable insights into various aspects of employee performance, such as productivity trends, departmental performance, the impact of internet connectivity, age-related trends, overtime distribution, and promotion rates.

Moreover, a study conducted by Alqahtani and Almaleh (2022), using machine learning models to predict employee promotions and identify the factors that affect employee promotion decisions. The study analyzed 54,808 employees of multinational companies in nine industries in Kaggle 2020. Based on this study, mutual information classification is the feature selection method. This approach evaluates the mutual information value of each variable and selects which variables have the highest information gain. The authors employed machine learning algorithms such as KNN, SVM, LR, Decision Tree, Random Forest, and Ensemble models, including AdaBoost and Gradient Boosting. They found that Gradient Boosting outperformed other classification algorithms and achieved an accuracy rate of 93.9%. Their results showed that the previous year's rating was the most critical factor affecting predicting employee promotions, while department tenure did not influence promotion decisions.

Another study conducted by Adeniyi et al. (2022) to compare the predictive capabilities of three distinct machine learning models in

forecasting employee performance using the Human Resource Dataset sourced from Kaggle repository. The classifiers compared are Decision Tree, Artificial Neural Network, and Random Forest. The dataset contained 311 instances, which were preprocessed through data cleaning, encoding, and Principal Component Analysis (PCA) to reduce the number of attributes from 36 to 20. The authors used evaluation criteria to compare the performance of the techniques, including accuracy, sensitivity, precision, F1-score, and Matthews correlation coefficient. Their results showed that the Artificial Neural Network performed better than other models, with an accuracy of 98.9%. The study recommended using Artificial Neural Network for performance prediction in organizations with ample resources and critical decisions. Random Forest could be used for medium resources, while Decision Tree was recommended for small resources and less critical decisions.

Emerging frameworks like the RanKer algorithm, Patel et al. (2022) introduced a novel method to classify employee performance based on various factors. The authors used a dataset of 1200 employees of a company called INX Future Inc. and identified 10 out of 28 features using a correlation matrix and principal component analysis (PCA). These selected features showed high correlation values with employee performance ratings and had high cumulative explained variance. The study compared several machine learning algorithms, including Decision Tree, Random Forest, Artificial Neural Network, and XGBoost. The authors merged these algorithms into a hybrid model using a voting classifier. The results showed that RanKer achieved the highest accuracy of 96.25% and performed better than the other methods in precision, recall, F1-score and AUC score.

Raza et al. (2022) aimed to study the organizational factors that influence employee attrition by using machine learning classifiers. They used the IBM HR Employee Attrition dataset, consisting of 1470 employee records and 35 features. The authors used four machine learning classifiers: Extra Trees, SVM, Logistic Regression, and Decision Tree. The feature selection method used was feature engineering, which included data correlation analysis and one-hot encoding. The results showed that the Extra Trees classifier performed better than other models in predicting employee attrition at 93%. Likewise, Wardhani and Lhaksmana (2022) conducted a study to predict employee attrition. They used the logistic regression method with feature selection and the IBM HR Employee Attrition dataset from Kaggle, which contains 1470 records and 35 attributes. They applied data preprocessing techniques such as data encoding, scaling and sampling using SMOTE-ENN. They compared three feature selection methods: Information Gain, Select K-Best, and Recursive Feature Elimination (RFE). To evaluate their models, they used a 10-fold cross-validation and ROC curve. They found that RFE achieved the highest accuracy of 0.853 and AUC of 0.925 with 20 selected features. In addition, they identified the top twenty features that influenced employee attrition.

By using three different machine learning classifiers, including Decision Tree, Artificial Neural Networks, and SVM, Mansor et al. (2021) attempted to predict employee attrition. IBM HR Employee Attrition dataset was used as sample data and consisted of 1,470 instances and 35 attributes. The study used three methods, namely correlation attribute, gain ratio attribute, and symmetric uncertainty attribute, to rank predictors of employee attrition. The study selected the fifteen most important features for modeling and reported on the challenges and limitations of using machine learning techniques to track employee attrition. The results

showed that the SVM model with the Pearson VII kernel function (PUK) had the highest accuracy among the three classifiers, reaching 88.87%.

While these findings substantiate the efficacy of ML methods for predicting employee performance or turnover, many studies still encounter overfitting, underscoring the necessity for more efficacious feature selection methods (Kamala and Thangaiah, 2019). High-dimensional datasets in the human resources (HR) domain have been shown to create persistent challenges (Nguyen et al., 2015). Researchers frequently resort to filter-based methods, such as correlation analysis (Mansor et al., 2021; Raza et al., 2022) or mutual information classification (Alqahtani and Almaleh, 2022), which can be efficient but risk excluding intricate interactions among variables. Alternatively, dimensionality reduction approaches, such as Principal Component Analysis (PCA) (Adeniyi et al., 2022; Patel et al., 2022) or stepwise regression (Alsubaie and Aldoukhi, 2024), are employed to reduce the size of large feature sets. In certain instances, specialized feature analysis tools (e.g., Feature Analysis Tool) are employed to detect and rank high-impact predictors (Jafor et al., 2023), while a number of studies adopt InfoGain or GainRatio-based methods to evaluate attribute importance systematically (Razali et al., 2023). Conversely, wrapper approaches, most notably Recursive Feature Elimination (RFE), have the capacity to yield more precise subsets; however, they are frequently computationally expensive and prone to overfitting when data size is limited or class distributions are skewed (Wardhani and Lhaksmana, 2022). As demonstrated in Table 2.3, a clear distinction emerges among these studies regarding their key findings, methodologies, results, and identified gaps, highlighting an ongoing need for robust and adaptive methods to address the complexities of HR datasets.

Table 2.3 Comparison of Previous Studies on Employee Performance Prediction

Author	Objective	Approach	Feature selection method used	Results	Potential Gap
Alsubaie and Aldoukhi (2024)	Predict employee attrition using the IBM Human Resource Analytics Employee Attrition and Performance dataset available on the Kaggle website (1470 records X 35 variables).	DT, RF, LR	Stepwise Regression	Logistic Regression (87.44%)	Did not use advanced feature selection methods
Ahmed et al. (2023)	Predict employee performance using two datasets: Employee Attrition dataset available on the Kaggle website (1200 records) and employee performance data from the Kenya School of Government database (206 real records).	KNN, DT, SVM, Gradient Boosting, and C4.5	dimensionality reduction techniques	SVM (98%)	Feature selection methods were not robust
Jafor et al. (2023)	predict employee promotion using the Employees Evaluation for Promotion dataset available on the Kaggle website (54,808 Records X 13 Attributes).	SVM, LR, ANN, RF, XGBoost, and AdaBoost	Feature Analysis Tool (FAT), Major and Minor feature-extracting techniques	The proposed model combines AdaBoost and ANN classifiers. (95.30%)	Lacked systematic benchmarking of classifiers
Razali et al. (2023)	predict employee productivity in higher academic institutions in Sarawak, Malaysia (103 instances X 16 attributes)	Linear Regression, RF Regressor, XGBoost Regressor, Decision Tree Regressor (TREE), MLP Regressor (MLP), SGD Regressor (SGD), and Voting Regressor (KNN).	InfoGainAttributeEval, GainRatioAttributeEval, CorrelationAttributeEval, OneRAttributeEval, and ReliefF	Linear Regression (MAE 0.4878 and MSE 0.4682).	Small dataset limits generalizability

Author	Objective	Approach	Feature selection method used	Results	Potential Gap
Alqahtani and Almaleh (2022)	predict employee promotion using the Employees Evaluation for Promotion dataset available on the Kaggle website (54,808 Records X 13 Attributes).	KNN, Logistic Regression, Decision Tree, RF, SVM, and Ensemble models (Adaboost and Gradient Boosting)	mutual information classification	Gradient Boosting (93.9%)	Limited feature selection method used
Adeniyi et al. (2022)	predict employee performance using the Human Resource Dataset obtained from the Kaggle repository (311 instances X 36 attributes)	Decision Tree, ANN, and RF	Principal Component Analysis (PCA)	ANN (98.9%)	Relied only on PCA for feature selection
Patel et al. (2022)	employee performance classification based on ratings using a dataset of 1200 employees working INX Future Inc. company (1200 employees X 28 Parameters)	RF, ANN, Decision Tree, XGBoost, and Ensemble Learning Approach (RanKer)	Principal Component Analysis (PCA)	RanKer (96.25%)	Focused on a hybrid voting classifier but lacked advanced feature optimizatio n
Raza et al. (2022)	predict employee attrition using the IBM Human Resource Analytics Employee Attrition and Performance dataset available on the Kaggle website (1470 records X 35 variables).	Extra Trees Classifier, SVM, Logistic Regression, and Decision Tree Classifier	data correlation analysis and one-hot encoding	Extra Trees Classifier (93%)	Did not benchmark advanced evolutionar y methods for feature selection
Wardhani and Lhaksman a (2022)	predict employee attrition using the logistic regression method with feature selection using the IBM Human Resource Analytics Employee Attrition and Performance dataset available on the Kaggle	Logistic Regression Classification (LR)	Information Gain, Select K-Best, and Recursive Feature Elimination (RFE)	LR with applying the RFE method (accuracy value of 0.853, and the AUC value is 0.925)	Focused on standard feature selection techniques

Author	Objective	Approach	Feature selection method used	Results	Potential Gap
	website (1470 records X 35 variables).				
Mansor et al. (2021)	predict employee attrition using the IBM Human Resource Analytics Employee Attrition and Performance dataset available on the Kaggle website (1470 records X 35 variables).	Decision Tree, SVM, and ANN	correlation attribute, gain ratio attribute, and symmetric uncertainty attribute	SVM (88.87%)	Did not address overfitting in feature selection

A robust alternative involves evolutionary algorithms, including Genetic Algorithms (GAs) proposed by Holland (1992), which iteratively refine solutions through five phases, as illustrated in Figure 2.2: initialization, fitness assignment, selection, crossover and mutation, thus identifying subsets of features that enhance model accuracy and interpretability (W. Ali and Saeed, 2023; Ghatasheh et al., 2022; Vijayanand and Devaraj, 2020). GA-based methods have been shown to be effective in a variety of optimization scenarios; however, their application in the field of HR analytics, particularly in the context of employee performance prediction, remains underutilized. Prior research often stops short of benchmarking multiple classifiers under a GA-based FS framework. Furthermore, studies that do apply GAs sometimes lack a systematic comparison against filter or embedded methods, leaving open the question of how best to combine GAs with leading machine learning (ML) algorithms (e.g. gradient boosting, XGBoost, random forest, support vector machines, k-nearest neighbours) to address the unique challenges of employee performance management (EPM), an area this study aims to advance.

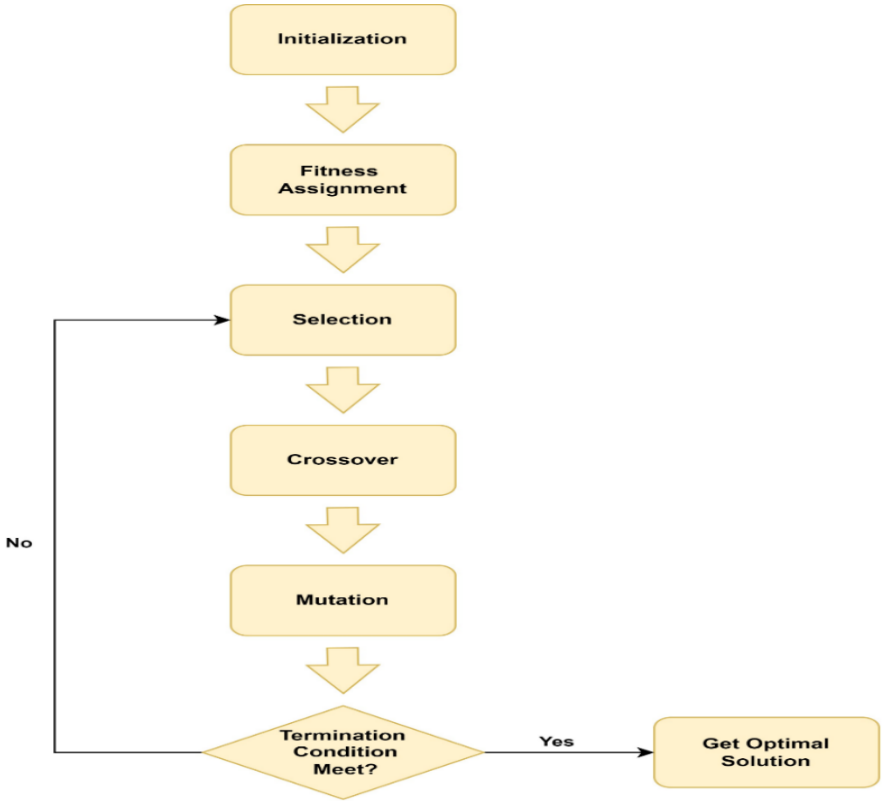


Figure 2.2: The Framework of Genetic Algorithm

2.3.3 AI-enabled Decision-Making Models

Artificial intelligence (AI) technology underwent exponential growth in the past decade, with most momentum derived from breakthroughs in machine learning (ML) with exemplary capabilities in pattern recognition, predictive analysis, and computerized decision support (Bughin et al., 2017; Makridakis et al., 2018). Typical use cases include predictive analysis for forecasting future events or trends, recommendation platforms, chatbots, and Robotic Process Automation (RPA), all with capabilities to displace or augment humans in jobs that have been under direct supervision (Lacity and Willcocks, 2016). In employee performance management (EPM), AI-facilitated decision support can have the potential for personalized feedback, real-time performance monitoring, and objective assessments of workers (Dalmia and Schatsky, 2019; Huang and Rust, 2018; Sánchez et al., 2022). With natural language processing (NLP) and

sentiment analysis, such a system can scan unstructured feedback from workers, identify areas for improvement, and actively drive HR interventions (Kang et al., 2020).

2.3.3.1 Explainable AI: Bridging the Interpretability Gap

Despite the high potential, AI-driven technology faces many social and ethical issues. Information security, algorithm bias, and transparency concerns have become particularly relevant in sensitive domains such as performance management (Mittelstadt et al., 2016). As such, added importance is placed on the value of explainable AI (XAI) in explaining sophisticated AI models in a manner that renders them intelligible, responsible, and in harmony with organizational values (Arrieta et al., 2020). Explainable AI (XAI) deals with the "black box" issue of many modern AI tools, namely deep learning and complex ensemble techniques (Angelov et al., 2021). Whilst these models can achieve high levels of predictive accuracy, the internal mechanisms that inform their decision-making processes are often opaque to the end-user. This opacity becomes problematic in the context of employee performance management, where high-stakes decisions such as promotions, layoffs, or targeted upskilling require transparent justifications to maintain trust and fairness (Holzinger et al., 2020).

XAI frameworks help to bridge the interpretability gap by offering actionable insights into the mechanisms that underpin specific predictions made by AI models. Tools such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) generate both local (individual prediction) and global (overall model behaviour) explanations, thereby clarifying how model features, ranging from performance records to demographic attributes, influence final decisions (Ali et al., 2023). To illustrate this point, consider a predictive model

identifying an individual as "high risk" for underperformance. XAI can then detail the specific task efficiency or interpersonal metrics that contributed to this rating, enabling more targeted interventions by managers (Chandra et al., 2023). Thus, XAI enhances interpretability and empowers HR stakeholders to make data-driven improvements that are aligned with organizational strategy.

While some AI models (e.g., Decision Trees and LASSO regression) inherently offer more transparency (Ranstam and Cook, 2018; Sokol and Flach, 2019), they may sacrifice predictive performance for interoperability. Conversely, highly accurate models like CatBoost or deep neural networks can be exceedingly complex, making them harder to interpret (Prokhorenkova et al., 2018). XAI was selected over competing approaches because it offers a compromise: retaining the predictive strength of advanced machine learning (ML) algorithms while augmenting them with interpretation layers. This balance is critical for employee performance management (EPM), where performance outcomes have substantial organizational and individual ramifications.

Furthermore, recent research highlights the synergy between XAI and human-in-the-loop design, emphasizing the collaboration between managers and HR professionals with AI to refine predictions and adapt them to the organizational context. For instance, causal AI models can deliver "what-if" analyses that allow HR leaders to simulate the potential outcomes of different interventions, thereby bridging the gap between raw predictive outputs and managerial decision-making (Angelov et al., 2021). Consequently, XAI fosters accountability and trust, thereby mitigating skepticism often arising from opaque algorithms in performance appraisals (Holzinger et al., 2020).

2.3.3.2 Advances in AI-enabled Decision-Making

Many have argued over AI redefining decision-making in industries over the years. J. Wu and Shang (2020) discussed techniques for uncertainty management in AI-facilitated decisions, and Cheng et al. (2022) argued about techniques for emotional intelligence in AI-facilitated performance frameworks and overcoming negativity towards them in workers. Yu and Li (2022) discovered that transparency in AI-facilitated decision-making positively contributes to employees' trust in AI, which aligns with a more significant move towards transparent approaches. Likewise, Nosratabadi et al. (2022) showed AI models boost recruitment, training, and other HR lifecycle aspects. Strich et al. (2021) focused on workers verifying working selves when AI is involved in performance appraisal. Drawing on these techniques, Salahat (2021) argued that empowered workers and knowledge management verify flexible decision-making. Cheng et al. (2022) showed that AI-enabled techniques yield competitive value and consequences for organizational performance. Wherein Paigude et al. (2023) collated these studies specifically for HR technology, strongly emphasizing predictive analysis, NLP, and chatbots for talent management.

Beyond the realm of direct HR applications, the literature points to structured frameworks such as Goal Hierarchical Tree (GHT) (Z. Han et al., 2021), Analysis Hierarchy Process (AHP) (Hilorme and Durmanov, 2019), and eXplaniable Plan Miner (XPlaM) (Alelaimat et al., 2023). Each of these offers a multicriteria or hierarchical perspective that integrates with predictive models to drive improvements in administrative procedures. They stand to benefit from XAI's interpretive capacity, ensuring that decisions derived through these frameworks are transparent and contextually relevant. Notwithstanding its potential, AI-enabled performance management faces systemic and ethical obstacles. Ensuring the quality and representativeness of the data is paramount for reliable

predictive outputs, as incomplete or skewed data can lead to erroneous conclusions (Mittelstadt et al., 2016). Algorithmic bias and privacy concerns pose further challenges, mainly if employee personal data are processed without robust safeguards (Hagendorff, 2020). Furthermore, many organizations lack the necessary infrastructure, funding and expertise to implement advanced AI systems successfully (Arntz et al., 2016). XAI plays an integral role in this regard, as interpretability mechanisms can reveal potential biases, enabling users to audit model behaviour and rectify issues proactively (Arrieta et al., 2020).

Furthermore, while specific models, such as Decision Trees, LASSO, and CatBoost with advanced encoding of categorical variables (Prokhorenkova et al., 2018), inherently possess a certain degree of explainability, the implementation of these models on a large scale necessitates the alignment of technical and organizational capacities. Recent advancements in interpretable neural architectures and federated learning hold promise for upholding data privacy and model explainability simultaneously, though these remain in their infancy within mainstream HR applications (Doshi-Velez and Kim, 2017; Rudin, 2019). Incorporating XAI into AI-enabled employee performance management systems offers a pathway to enhance interpretability and address critical concerns of fairness and trust. In the context of organizations seeking to bridge the gap between predictive modelling and decision-making, the potential of XAI to render high-level machine learning (ML) algorithms more accessible and actionable for human resources (HR) professionals and managers is evident. By delineating the precise factors underpinning a predictive score – such as work experience, task completion rates, or peer-review scores – XAI facilitates more informed resource allocation, skill development programs, and broader strategic decisions.

Consequently, the subsequent generation of performance management solutions should proactively integrate XAI design principles and user-centric approaches. By identifying and mitigating algorithmic biases, ensuring robust data governance, and engaging employees and managers in the human-AI collaboration loop, companies can move towards a more accountable and responsive EPM system. Research by McKinsey Global Institute and others highlights the significance of mental health considerations and data ethics in emergent HR technologies, further reinforcing the need for holistic frameworks that balance technological innovation with organizational well-being.

2.4 Summary

This comprehensive review identified the most significant gap as the lack of a general framework that systematically integrates the broad range of factors affecting employee performance within Bahrain's government sector. Previous studies have examined various elements, such as leadership commitment and communication, but none has constructed a holistic model encompassing Bahrain's distinct administrative environment. Addressing this shortfall is crucial in light of ongoing initiatives to develop public servants and align governmental services with national and global performance benchmarks.

The existing literature also shows that Bahraini public-sector research rarely uses advanced or predictive methods to investigate and anticipate employee performance. Most studies rely on cross-sectional or qualitative designs, which limits their ability to uncover long-term patterns and mitigate potential biases in areas such as recruitment and performance evaluation. The high-dimensional nature of HR datasets further complicates these efforts: conventional techniques may overlook complex

variable interactions, resulting in models that are less nuanced and potentially less accurate.

Another issue is the challenge of optimal feature selection, a process essential to avoiding overfitting and ensuring that performance predictions remain both stable and reliable. Many studies employ classical filter-based approaches, which can inadvertently increase model complexity or exclude important predictors. Genetic algorithms (GAs) offer a promising, iterative solution for refining feature sets, but few investigations have systematically applied GA-based techniques in a public-sector context, leaving their practical advantages underexplored.

Additionally, although a variety of machine learning (ML) algorithms, including Random Forest, XGBoost, and Support Vector Machines, demonstrate potential in human resource analytics, there is little uniformity in their comparative evaluation. This lack of standardization means that the most effective algorithm or combination of algorithms, particularly when coupled with robust feature selection, remains unknown for predicting employee performance in Bahrain's public sector. A further, closely related gap is the inadequate attention to the explainability of AI-powered models in employee performance management. Advanced AI methods, particularly those leveraging deep learning or complex ensembles, offer impressive predictive accuracy but often function as "black boxes," making it difficult for HR managers and employees to understand how decisions, such as promotions or targeted upskilling, are reached. Explainable AI (XAI) frameworks are the answer. These frameworks elucidate specific features, such as performance records or demographic attributes, shape model outcomes. This transparency is vital in high-stakes contexts where fairness and trust must be preserved. If an employee is flagged as "high risk" for underperformance, XAI can pinpoint the relevant performance metrics that

contributed to this designation. Despite XAI's relevance for enabling data-driven yet equitable HR practices, few studies have systematically integrated these methods into predictive models tailored for the Bahraini public sector.

This study presents a game-changing AI-enabled framework tailored to the Bahraini public sector. It incorporates genetic algorithm-based feature selection across multiple ML classifiers and emphasizes explainable analytics. The model unites widely recognized performance drivers into a single, highly customized model for the Bahraini governmental setting. This study establishes a new standard of predictive precision, policy relevance and interpretability. This framework builds on prior findings, highlighting the pivotal roles of managerial support and effective communication, and extends them by employing innovative, data-centric strategies grounded in XAI principles. This integrated approach promises both theoretical growth and tangible benefits for local policymakers and practitioners committed to advancing employee performance management in a dynamic, rapidly evolving public service environment.

Chapter 3
Research Methodology

3.1 Overview

This chapter outlines the research methodology, and the specific methods employed to examine employee performance management in Bahrain's public sector. After establishing the theoretical underpinnings of the study, the chapter discusses the methodological decisions made to ensure a rigorous approach. In doing so, the researcher adapted the Research Onion framework proposed by Saunders et al. (2019) to achieve consistency and clarity throughout the process. Babbie (2020) notes that such a structured model helps systematically organize and align philosophical positions, research strategies, and procedural steps. In addition, this chapter addresses ethical considerations pertinent to data collection and analysis, along with the measures implemented to improve the reliability and validity of the resulting findings.

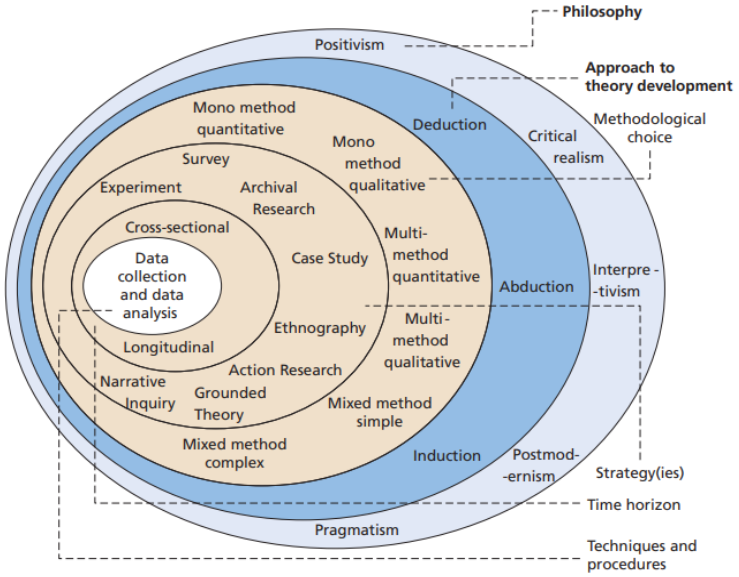


Figure 3.1: The 'research onion',
(Source: Saunders et al. (2019))

3.2 Research Philosophy

The study adopted a specific research philosophy to ensure coherence in both the qualitative and quantitative facets of its sequential exploratory mixed-methods design. By aligning underlying assumptions about reality, knowledge, and valid methods of inquiry, the researcher could objectively examine the factors affecting employee performance in Bahrain's public sector while also remaining open to interpretive insights. In this regard, it was assumed that such factors could be discerned through systematic and evidence-based procedures, albeit with recognition that social contexts introduce complexity. This stance parallels the realist and objectivist position often associated with positivism, where careful data collection and critical analysis are seen as pathways to uncover underlying trends or causal relationships (Saunders et al., 2019).

Ontology and epistemology provided the cornerstone for determining how best to integrate the qualitative and quantitative stages. Ontology, the philosophical consideration of what constitutes reality, led to the view that organizational and employee-level performance drives such as leadership commitment, workplace culture, and personal competencies existed independently of individual perceptions and could be uncovered through empirical methods (Seale et al., 2011). Meanwhile, an objectivist epistemology guided how knowledge would be gathered and validated, drawing on the idea that common reality can be systematically studied with robust methodological tools (Crotty, 1998). Even though interpretation remains a central component in any inquiry, the study's design allowed the researcher to move from a qualitative exploration of public-sector performance issues to a structured and testable quantitative model.

Building on these philosophical underpinnings, the study adopts a hybrid epistemological stance that bridges positivist and interpretivist

traditions. While predictive modeling adopts a post-positivist approach, assuming a single, objective reality that can be known only imperfectly (Creswell and Plano Clark, 2018), the integration of qualitative data, such as cultural nuances identified through focus group discussions, aligns closely with constructivist principles, recognizing knowledge as socially constructed and inherently value-laden (Lincoln and Guba, 1985). This hybrid epistemological stance acknowledges the deterministic outputs of AI-driven analyses while simultaneously preserving human-centric subjectivity in defining "performance," thus ensuring algorithmic insights remain contextually and culturally informed (Johnson and Onwuegbuzie, 2004). Such an integrated epistemological approach is essentially pragmatic, reflecting the underlying paradigm frequently adopted in mixed methods research (Tashakkori and Teddlie, 2010). Pragmatism serves as a philosophical foundation that bridges the strengths of post-positivist rigor, objectivity, and generalizability with constructivist emphasis on context, interpretation, and nuanced meaning-making (Morgan, 2014). By explicitly acknowledging this dual epistemological positioning, the research maintains philosophical coherence, methodologically leveraging both quantitative precision and qualitative depth. This ensures empirical rigor and interpretive validity, aligning AI-enabled predictive modeling results with an informed, culturally sensitive, and human-centered definition of employee performance.

3.3 Research Approach

Researchers most frequently employ one of two approaches – deductive or inductive – when designing their studies (Blaikie and Priest, 2019). In the case of the deductive approach, researchers commence with established conceptions or frameworks, subsequently applying them to new information collected (Babbie, 2020). Conversely, under the inductive

approach, the development of theoretical constructions assumes primacy, with trends in information guiding the development of generalized constructs (Bryman and Bell, 2015). Despite their discrete nature, both inductive and deductive approaches can be utilized in conjunction (Saunders et al., 2019). In some instances, inductive frameworks can first be used to inform an inquiry into significant phenomena, and then inductive investigation can be used to develop and build upon what arises out of the information (Seddighi, 2012).

The present study employs a sequential exploratory mixed-methods design, examining employee performance management within Bahrain's public sector. The research commenced with an inductive approach, utilizing qualitative methods such as a systematic literature review, expert interviews, and focus group discussions, to identify salient performance factors and address the research questions in contexts where knowledge was already limited. These qualitative findings then informed a subsequent deductive phase, wherein quantitative data were collected to investigate further and validate emerging insights. While the study was not structured around testing specific hypotheses, the deductive elements still allowed the researcher to determine how well initially identified themes aligned with larger patterns or theoretical propositions relevant to public service performance.

This dual-phase approach was implemented to overcome the shortcomings of relying exclusively on inductive or deductive reasoning (Buchanan and Bryman, 2007). In the inductive stage, fresh insights emerged, allowing adaptability and effectively highlighting Bahrain's administrative landscape's complexities and cultural subtleties. Conversely, the deductive strand was instrumental in enhancing generalizability, thereby enabling the researcher to verify the consistent

relevance of the identified factors across diverse areas of the public sector. Tashakkori et al. (2020) posit that this amalgamation of inductive and deductive logic is particularly well-suited for mixed-methods inquiries, thereby enabling studies to address multifaceted research questions in a coherent, evidence-based manner.

3.4 Time Horizons

This study employed a cross-sectional time horizon. As described by Saunders et al. (2019), a cross-sectional approach represents a “snapshot” of the phenomenon under investigation at a specific point in time. This design was especially appropriate given the practical constraints on data collection within the Bahraini public sector. The researcher had a limited window of access to potential respondents, making it impractical to conduct multiple waves of data collection over an extended period.

While longitudinal studies can yield detailed insights into how factors evolve over time, this option was not feasible here due to time constraints and the administrative realities associated with securing long-term involvement from public-sector employees. Consequently, certain activities typical of a longitudinal design, such as repeated follow-up measures, were omitted to accommodate the tight schedule and resource limitations. Despite these limitations, the chosen cross-sectional design enabled the collection of robust data from a broad sample, thus meeting the core objectives of investigating key factors related to employee performance in the Bahraini public sector.

3.5 Research Strategy

Achieving consistency between the research questions, methodology, and theoretical foundation is pivotal when examining employee performance in Bahrain's public sector. Collins (2018) asserts that this consistency can be established by selecting a well-defined research strategy that clarifies

the overall direction of an investigation. Bryman (2016) further asserts that researchers frequently opt for strategies such as surveys, case studies, action research, or archival methods to address their specific objectives.

Within the sequential exploratory mixed-methods design of the present study, as illustrated in Figure 3.2, an initial qualitative phase (involving a literature review, expert interviews, and focus group discussions) was followed by a quantitative phase employing a survey. The survey collected data from a substantial number of public sector in Bahrain, with the objective of testing and generalizing emerging insights from the qualitative stage. This strategy was underpinned by the understanding that surveys possess the efficiency to gather data from larger samples, thereby enhancing the representativeness of findings and contributing to a more comprehensive understanding of the qualitative findings (Babbie, 2020)

Despite the occasional critique of surveys for producing superficial data (Saunders et al., 2019), the study addressed this concern by formulating comprehensive and theory-informed survey questions grounded in the preceding qualitative phase. This methodological approach ensured that each survey question addressed critical domains of employee performance, thereby producing data sufficiently rich to inform evidence-based recommendations for public sector organizations. In addition, it allowed for deeper exploration of performance-related issues that might not be fully captured by structured questionnaires. The employment of a dual-pronged strategy, encompassing qualitative inquiries to elucidate contextual nuances and a large-scale survey to validate and generalize findings, ensured the attainment of substantial and comprehensive conclusions regarding employee performance management within Bahrain's public sector.

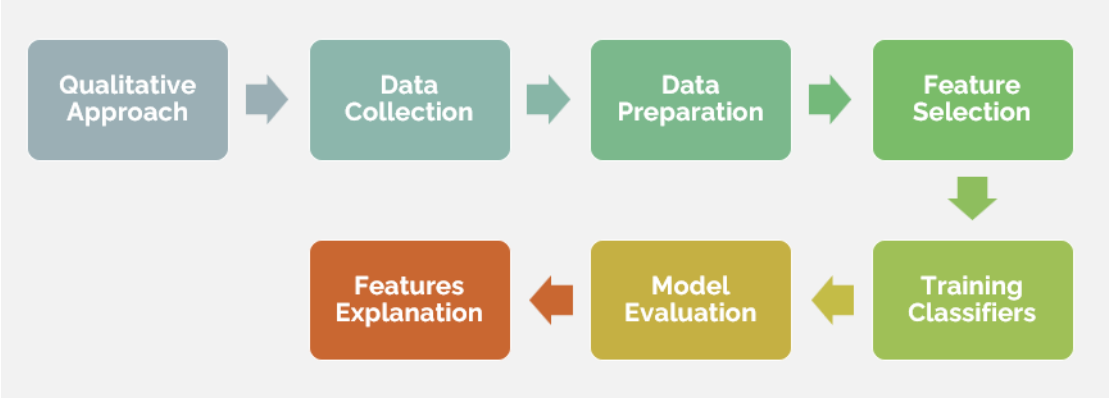


Figure 3.2: Study Framework

3.6 Research Design

A sequential exploratory mixed-methods design was adopted to achieve a comprehensive understanding of the research problem and fulfill the study's objectives. As defined by Creswell and Plano Clark (2018), such a design involves two distinct phases: a qualitative phase followed by a quantitative one, integrating the strengths of both paradigms in a complementary fashion. In the first stage, qualitative data were collected and analyzed to explore the factors influencing employee performance within the Bahraini public sector. This phase employed expert interviews and focus group discussions (FGDs), enabling the researcher to capture contextually nuanced insights and address both theoretical and practical dimensions of performance.

In the second phase, a structured survey was developed to quantitatively examine and validate the themes and performance factors that emerged during the qualitative stage. The survey was administered across a broad sample of public sector employees in Bahrain. This phase aimed to test the relevance and predictive strength of the identified performance factors by developing an AI-enabled predictive model tailored to Bahrain's public workforce. This design was especially suitable for three primary reasons.

First, initiating the inquiry with qualitative methods enabled the study to uncover in-depth perspectives grounded in Bahrain's unique administrative, institutional, and cultural environment (Creswell and Plano Clark, 2018). Second, the integration of qualitative findings into the quantitative design fostered methodological synergy, allowing contextually emergent themes such as organizational culture, leadership practices, and employee autonomy to be operationalized and empirically tested through predictive modeling (Tashakkori and Teddlie, 2010). Third, the design's iterative movement between exploration and confirmation enhanced the study's internal validity, contextual relevance, and practical applicability. As Bryman (2006) emphasizes, such cyclical movement is a hallmark of strong mixed-methods inquiry, especially in applied fields like public administration.

Aligned with this overarching methodology, the multi-stage design ensured a rigorous, structured, and participatory process for identifying, contextualizing, and analyzing factors shaping employee performance in Bahrain's public sector. A wide array of qualitative and quantitative techniques was methodologically integrated to generate robust, stakeholder-informed, and data-driven insights, supporting both theoretical advancement and actionable outcomes.

Beyond its procedural rationale, the research design was fundamentally shaped by the study's dual epistemological orientation, integrating both constructivist and post-positivist perspectives. The initial qualitative phase aligned with constructivist principles by recognizing employee performance as a context-dependent construct, best understood through the subjective interpretations of stakeholders within the Bahraini public sector. This phase emphasized the value of participant narratives in uncovering culturally embedded meanings and performance expectations. In contrast,

the subsequent quantitative phase adhered to a post-positivist logic, applying AI-enabled predictive modeling techniques to test, validate, and generalize those insights using structured data.

This philosophical duality was not abstract but directly informed key methodological decisions. For instance, the performance factors identified through the Genetic Algorithm (GA) in the modeling phase were not accepted at face value; instead, they were cross-validated against qualitative findings to ensure contextual relevance. When features such as "Hybrid Work Models" or "Appraisal Systems" emerged from the GA, they were traced back to expert interviews and FGDs to confirm their practical significance in the Bahraini context. Similarly, AI model outputs—such as variable importance rankings from Random Forests or SVMs—were interpreted through the lens of qualitative themes (e.g., organizational culture, autonomy, or leadership), adding explanatory depth to statistical patterns. Moreover, the survey instrument used in the quantitative phase was designed not only from theoretical frameworks but also grounded in stakeholder language and priorities uncovered during qualitative data collection. This ensured that the constructs being measured were both academically valid and socially meaningful.

This approach strengthened the study's ability to produce results that are not only empirically sound but also grounded in the lived realities of Bahrain's public sector environment.

3.6.1 Qualitative Approach

As demonstrated in Figure 3.3, the model was initiated with a systematic literature review (SLR) to establish a strong theoretical foundation and identify recognized factors globally and locally in the extant body of knowledge. The subsequent stage involved expert interviews conducted to refine contextual relevance and uncover potential new variables grounded

in the realities of public administration in Bahrain. The investigation then proceeded with a move towards focus group discussions (FGDs) to allow participants to review, challenge, and consolidate proposed factors. In an iterative manner, any discrepancies in information developed in earlier phases were resolved and facilitated a mechanism for a search for a consensus. The amalgamation of these factors resulted in a comprehensive scheme with theoretical and empirical underpinnings affecting employee performance.

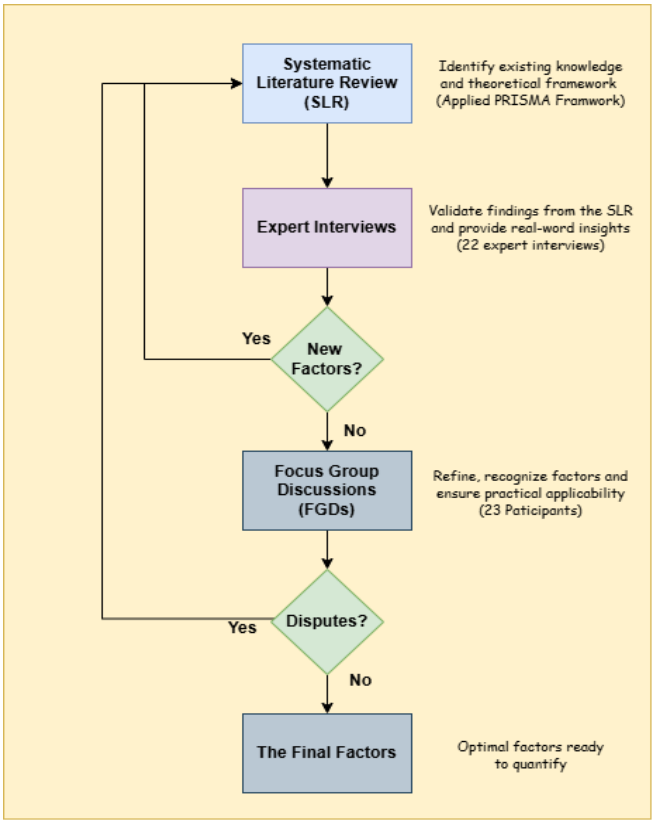


Figure 3.3: Qualitative Research Methodology

As the procedures and methods of the systematic literature review (SLR) have already been comprehensively delineated in the preceding chapter, the focus of the researcher shifts to the subsequent phase of the sequential exploratory design, namely the expert interviews. These interviews are pivotal in contextualizing and refining the factors derived

from the SLR, ensuring alignment with Bahrain's unique public-sector environment and validating the applicability of each identified variable.

3.6.1.1 Expert Interviews

This stage of this study has been involved conducting expert interviews to validate and contextualize the factors identified in the systematic literature review (SLR). These interviews directly contributed to the broader research goals by bridging the gap between theoretical constructs and practical application in Bahrain's public sector. By engaging experts with extensive experience and diverse roles, this stage ensures that the findings are grounded in real-world contexts (Bryson et al., 2014), offering actionable insights that align with the unique socio-administrative dynamics of Bahrain. The interviews refine and optimize the list of factors, identifying those most relevant for measuring and improving public servant performance while addressing gaps or limitations in the existing literature.

1. Expert Selection Process

Experts were selected using a purposive sampling approach, a widely recognized strategy for identifying participants with in-depth knowledge and experience relevant to the phenomenon under study (Patton, 2015; Teddlie and Yu, 2007). In Bahrain's public sector context, this method allowed the deliberate targeting of individuals capable of providing nuanced, sector-specific insights that might not emerge from a purely random sample (Creswell and Creswell, 2018). Initially, a pool of 40 potential candidates was generated through professional networks, academic collaborations, and recommendations from senior officials. The researcher then assessed each candidate against predefined criteria - professional experience, sectoral representation, and contributions to policy-making or human resource practices - to ensure that participants met

the information-rich criteria of purposive sampling (Palinkas et al., 2015). After further evaluating each candidate's availability and willingness, 22 experts were ultimately shortlisted. These individuals came from diverse hierarchical levels, ministerial functions, and professional backgrounds, reflecting the heterogeneity often advocated in qualitative research for generating well-rounded, contextually informed data (Patton, 2015). This careful selection process maximized the study's relevance and credibility and provided the depth of understanding necessary to analyze performance dynamics across Bahrain's public sector.

The experts were selected for their extensive experience and academic credentials, ensuring they had a solid understanding of public administration's structural and operational facets. Participants had to have at least 20 years of experience (Tummers and Rocco, 2015) and relevant professional or academic qualifications (Freeman and Auster, 2011), preferably holding advanced degrees in public administration, human resource management, or business analysis. This strategy was designed to create a knowledgeable and experienced group of experts capable of illustrating how organizational structures influence employee performance in practical settings.

Further to these core requirements, efforts were made to incorporate a diversity of roles and policy-making expertise. The expert panel encompassed individuals from a spectrum of hierarchical levels, including assistant undersecretaries, advisors, and operational staff (Ospina and Foldy, 2010). This diversity was vital to capturing a complete view of how policies and HR interventions are conceptualized at the executive level and how they materialize in the day-to-day operations of public institutions (Bryson et al., 2014). Moreover, participants were drawn from multiple sectors – namely education, health, labour, and social development – to

comprehensively cover Bahrain's public-service landscape (Christensen and Lægreid, 2011).

Each expert had to meet selection criteria and confirm availability and a willingness to adhere to the study's timeline. This ensured reliable and continuous participation throughout the data-collection phases (Flick, 2012). Credibility and reputation were also considered, with a particular emphasis on recognized leaders with a demonstrated record of impactful contributions to the public sector (Gläser and Laudel, 2009). The amalgamation of these considerations resulted in forming a team of experts who offered both depth and breadth of perspective. This ensured the study's analysis of performance dynamics in Bahrain's public sector was enriched.

2. Expert Interview Preparation and Protocol

Following the selection of experts, the interview process commenced with the development of a semi-structured interview guide, a method known to strike a balance between covering essential themes and allowing interviewees the flexibility to express relevant insights (Brinkmann and Kvale, 2018). This guide, as shown in Appendix (A), was sent to each participant ahead of time to familiarize them with the purpose of the study, the sequencing of ideas, and the 54 performance-related factors derived from the previous literature review. Providing both closed and open-ended questions ensured coverage of specific issues (e.g., factor applicability) while also leaving room for the emergence of new, context-specific insights (Creswell and Plano Clark, 2018). Experts were explicitly assured of confidentiality, consistent with standard ethical guidelines that emphasize safeguarding participant anonymity and data security (Wiles, 2012). Given that research in multilingual contexts can introduce translation complexities, a process of procedural definition and consultation with language specialists was undertaken to clarify potentially

overlapping or ambiguous factor labels (Temple and Young, 2004). This thorough preparation aimed to foster a focused yet flexible exchange of ideas and to respect participants' valuable time, as recommended in high-quality qualitative research (Patton, 2015).

3. Data Collection and Validation

To accommodate varying schedules and preferences, interviews were conducted through face-to-face meetings, videoconferencing, or email exchanges, which aligns with emerging best practices in qualitative inquiry that prioritize participant convenience and richness of data (Leedy and Ormrod, 2016). All interactions were audio-recorded (or saved in written form, in the case of emails) and systematically documented through detailed field notes (Creswell and Creswell, 2018). After each interview, participants received a summarized transcript of their remarks, a process often termed member checking or respondent validation, which enhances the credibility of qualitative findings by ensuring that participants can confirm or clarify their perspectives (Lincoln and Guba, 1985). Interviews continued until data saturation was achieved, defined here as the point at which no fundamentally new information emerged, consistent with accepted practice in qualitative research (Guest et al., 2006). Specifically, after interviewing 18 experts, thematic redundancy became evident; however, four additional interviews were conducted to validate this saturation, reaching a total of 22 interviews, and data saturation was explicitly monitored using NVivo's frequency and thematic coding capabilities. The analysis revealed that, by the 18th interview, new thematic codes became infrequent, and after the 20th interview, no fundamentally new themes emerged, as confirmed quantitatively by stable frequency counts across all coded interviews. Therefore, after conducting 22 expert interviews, it was objectively confirmed through the NVivo

coding framework that saturation had indeed been reached, ensuring comprehensive thematic coverage and is methodologically justified. Qualitative research literature indicates that data saturation often occurs within the first 12–20 interviews in relatively homogeneous samples. For instance, Guest et al. (2006) found that most thematic insights can be uncovered within a dozen or so interviews, while Saunders et al. (2018) emphasize that stopping data collection once no new information is gleaned is a sound practice to ensure sample sufficiency and research rigor. In line with these guidelines, the decision to cease conducting further expert interviews with 22 participants (after confirming saturation at Interview 18) ensured that the study gathered enough data to cover all relevant themes without unnecessary additional interviews.

Although scheduling constraints proved challenging, consistent and transparent communication helped overcome these obstacles. The additional steps of clarifying translation ambiguities and verifying experts' perspectives enhanced the data's trustworthiness and underscored the rigorous, participant-centered approach fundamental to robust qualitative inquiry (Bryman, 2016).

4. Thematic Analysis of Expert Interview Data

Thematic analysis is a robust qualitative analytic method frequently recommended for identifying, organizing, and interpreting patterns within datasets (Braun and Clarke, 2006; Nowell et al., 2017). It was employed to analyze the data obtained from expert interviews during the second research stage. The analysis was conducted systematically using NVivo's leading software for qualitative research, with the aim of refining and validating the 54 initially identified factors influencing employee performance. The analysis followed the six-phase framework proposed by Braun and Clarke (2006), adapted to accommodate the specific features

and research goals of this study, thus ensuring methodological rigour and relevance (Creswell and Creswell, 2018).

Initially, the familiarization phase entailed the importance of each interview transcript into NVivo for meticulous review, accompanied by the rechecking of audio recordings to ensure accuracy and the highlighting of key insights. Through this process, the researcher was able to gain a profound understanding of expert perspectives on performance appraisal mechanisms, job security, and hybrid work models (Patton, 2015). Subsequently, initial coding was conducted utilizing NVivo's tagging tools to systematically categorize significant phrases, sentences, and ideas. To enhance reliability, two coders independently coded a subset of the transcripts and achieved an inter-coder reliability with a Cohen’s Kappa ($\kappa = 0.83$), demonstrating high consistency in the thematic analysis. These codes ranged from "Job Security" to "Commute and Accessibility," thus capturing relevant data points and recording expert recommendations on modifying or merging factors. In the third phase, the study identified potential themes by grouping related codes, leveraging NVivo's query and categorization features to detect patterns such as "Hybrid Work Models," "Organizational Structure and Clarity," and "Balanced Sanction Systems." These emergent themes underwent refinement during the review phase, wherein the thematic clusters were assessed against the broader dataset to ensure coherence and alignment with expert views (Flick, 2012). For instance, related topics such as "Technological Advancement," "Technological Competence and Support," and "Integration of Technology and Work Practices" were consolidated into "Technological Integration" to capture expert feedback more holistically. Themes pertaining to mental health and workplace well-being were similarly consolidated under "Well-being and Mental Health," following the principle of creating meaningful,

comprehensive thematic clusters (Clarke and Braun, 2013). Subsequently, each theme was defined and named, drawing on both the experts' statements and relevant theoretical perspectives. For instance, the theme "Flexible Working Hours" was formulated to reflect the potential for boosting employee productivity and reducing stress, an insight which resonates with the operational context of Bahrain's public sector (Guest, 2014). Detailed definitions, along with selected excerpts from the interviews, were stored in NVivo to document the scope and depth of each theme. The final analysis of the study was then synthesized into a cohesive report supported by NVivo's thematic maps, hierarchical charts and word clouds, which illustrated relationships such as the link between "Job Security" and "Employee Retention", thus confirming the overall validity of the findings and demonstrating how expert testimony could inform practical recommendations (Bazeley and Jackson, 2013).

This comprehensive approach enabled the confirmation of predefined factors and the identification of novel themes, including nuanced relationships between workplace accessibility and employee stress, as well as cultural challenges surrounding hybrid work models in Bahrain. By employing NVivo to conduct a systematic and transparent analysis, the researcher ensured that all expert testimony was accurately captured, interpreted, and ultimately aligned with the study's overarching goal of enhancing employee performance within the Bahraini public sector. This combination of meticulous qualitative analysis and software-assisted organization thus provides a substantial evidentiary foundation for the formulation of informed, context-sensitive policy and human resources interventions (Bryman, 2016; Lincoln and Guba, 1985).

With these expert-driven revisions in place, the next stage of the study will focus on integrating and validating the consolidated factors through

quantitative measures and further participatory methods. This continuous, iterative process guarantees that the final model aligns with academic best practices and resonates with Bahrain's public sector's lived realities and policy objectives.

3.6.1.2 Focus Group Discussions (FGDs)

Building upon the findings of the extensive literature review and the expert interviews, this third stage involved an in-depth categorization of the identified factors influencing employee performance in Bahrain's public sector. Research indicates that thematically organizing factors into coherent groups not only enhances theoretical clarity but also enables more effective implementation of performance improvement strategies (Herzberg, 1969; Maslow, 1943). Consequently, the study undertook a systematic process to cluster the factors emerging from the previous phases, ensuring that each grouping reflected strong conceptual underpinnings from established theories such as Herzberg's Two-Factor Theory, Maslow's Hierarchy of Needs, and the Job Demands-Resources Model (Bakker and Demerouti, 2007; Becker, 2010).

This categorization serves as a foundational step by translating generalized research findings into an actionable framework that can be adapted to the Bahraini context. Notably, grouping related variables helps researchers and practitioners target specific areas, such as "Motivation and Engagement" or "Organizational Culture and Governance", with interventions tailored to local cultural, administrative, and policy requirements (Ritz et al., 2016). Each category thus aligns with both theoretical constructs and practical realities, thereby ensuring the resulting model's applicability to the unique dynamics of Bahrain's public sector.

To validate and refine the proposed categories, the study employed Focus Group Discussions (FGDs), a qualitative approach endorsed for

capturing nuanced perspectives within a collective setting (Krueger and Casey, 2015). Focus groups were particularly suitable here because they encourage real-time interaction, allowing participants to debate, reconsider, and synthesize ideas in a manner that can illuminate context-specific challenges and opportunities in the Bahraini public sector (Patton, 2015). The following paragraphs detail the participant selection, procedures, and analysis steps undertaken to ensure robust and methodologically sound findings.

1. Participant Selection

A total of 23 public sector employees participated in four focus groups, supplemented by a subset of retired senior officials for historical and strategic insights. These individuals were selected using purposive sampling, ensuring diverse backgrounds in roles such as frontline service, management, policy-making, and human resources (Teddlie and Yu, 2007). To maintain data quality, inclusion criteria required at least 15 years of relevant experience, a high level of sector-specific knowledge, and willingness to engage in critical discussions around performance-related factors (Fithri et al., 2024). This approach allowed the study to capture breadth and depth of perspectives, thereby aligning with best practices in qualitative research (Guest et al., 2006). Demographic summaries of the interview and FGD participants (anonymized by role and sector) are provided in Appendix (B) to enhance transparency about the sample composition.

2. Focus Group Procedures

Participants were divided into four groups of 4-6 individuals each, ensuring a manageable group size that fosters in-depth dialogue (Krueger and Casey, 2015). To begin, a comprehensive list of the factors was distributed, accompanied by succinct definitions for clarity. The session opened for

90–120 minutes by reiterating the study's purpose: to refine and contextualize the categorization of performance factors while emphasizing confidentiality and equal participation.

During the categorization exercise, participants were encouraged to assign the factors to the category they deemed most fitting. These allocations were visualized using sticky notes, digital collaboration tools, or both, promoting collaborative debate and transparent decision-making (Nyumba et al., 2018). Whenever discrepancies arose, such as whether "Employee Well-being" belonged under "Motivation and Engagement" or "Workplace Environment and Support", the group reached consensus through guided discussion and, in some cases, a brief voting process. By rotating the categories among the four groups, the study enabled cross-validation, mitigating potential biases and reinforcing the reliability of the categorization framework (Krueger and Casey, 2015).

3. Data Collection and Validation

All focus group sessions were audio-recorded for accuracy and transcribed verbatim. Participants received copies of their group's consolidated assignments, as well as summaries of key discussions for member checking, a practice that enhances the credibility of qualitative data by allowing participants to verify or clarify their contributions (Lincoln and Guba, 1985). Additionally, the researcher assigned two independent researchers to perform an expert review of the transcripts, comparing the emergent insights with both the original theoretical framework and data from earlier expert interviews (Creswell and Creswell, 2018). Thematic saturation was achieved by the fourth focus group (FGD). By the time this fourth FGD was conducted, participants' contributions had become repetitive, with no substantively new ideas emerging. Accordingly, data collection was concluded after four focus groups, for a total of 23

participants across all sessions. This sample size and stopping point were guided by the saturation principle, as further sessions were deemed unlikely to yield additional insights.

Methodologically, this threshold is supported by qualitative research guidelines: studies have shown that the majority of new themes in focus group research typically emerge in the first few groups. In practice, conducting four FGDs falls within the recommended range (often about 3–6 groups), sufficient to capture diverse perspectives in a fairly homogeneous population. Thus, ending the focus group phase at the point of saturation ensured both efficiency and completeness. This approach aligns with best-practice recommendations that researchers can confidently halt data collection once informational redundancy is reached (Guest et al., 2006), thereby upholding rigor while avoiding over-sampling.

4. Analysis of Focus Group Outcomes

The finalized lists and notes from each group were collated in NVivo. Methodological rigor was ensured through member checking, where participants reviewed and confirmed their inputs, and through inter-coder reliability analysis with NVivo, yielding a Cohen's Kappa of 0.86, enhancing the empirical strength and contextual validity of the study. The quantitative element involved counting the frequency with which each factor was placed in a particular category, while the qualitative dimension entailed coding the justifications and debates participants shared (Bryman, 2016). This dual analysis revealed not only the strength of certain category-factor alignments but also subtle overlaps or emerging facets requiring further inquiry. Where ambiguity persisted, for instance, regarding factors such as "Work-Life Balance" or "Organizational Citizenship Behaviors", additional expert consultation was sought.

Finally, each category's label and definition were revised as needed to reflect collective participant feedback. For example, if participants consistently reported that "Team Dynamics and Peer Relationships" placed undue emphasis on interpersonal connection, it could be renamed "Team Dynamics and Peer Influence" to capture its broader organizational impact. These refinements underscore the adaptive and iterative nature of qualitative research, aligning with recommendations that categories should evolve in tandem with participant input (Patton, 2015).

At this stage, the study produced a consensus-based framework of seven categories, comprising both theoretical underpinnings and context-specific insights, that is poised to guide subsequent quantitative analyses. Accompanying this framework is a detailed report, as illustrated in the Appendix (C), documenting the expert interviews and focus group procedures, key modifications, and justifications for all changes. These deliverables not only crystallize the findings but also maintain an audit trail, allowing future researchers or stakeholders to trace the evolution of the categorization process (Bryman, 2016). This stage underscores the study's commitment to methodological integrity and practical relevance.

By data triangulation, systematically integrating theory, expert insights, and participant perspectives, the research establishes a robust, context-aware framework for understanding and enhancing employee performance in Bahrain's public sector, one that balances academic rigour with pragmatic applicability (Bakker and Demerouti, 2007; Ritz et al., 2016).

This data triangulation is employed in this study as a validity technique to strengthen qualitative findings. In academic terms, triangulation refers to using multiple data sources or methods to gain a comprehensive understanding of a phenomenon (Denzin, 2017; Patton, 2015). It is

essentially a strategy to test the consistency and credibility of results through the convergence of information from different sources. By comparing and cross-verifying evidence from independent sources, triangulation helps mitigate interpretive bias, the risk of conclusions being skewed by any single perspective. In qualitative research, where analysis is inherently interpretive, this approach enhances credibility by ensuring that insights are not an artifact of one dataset or a researcher's viewpoint (Creswell and Plano Clark, 2018; Flick, 2012). In other words, converging multiple lines of evidence serves as a safeguard against subjective misinterpretation, thereby increasing the trustworthiness of the findings.

In practice, the study implemented a triangulation strategy by integrating data from the systematic literature review, expert interviews, and focus group discussions (FGDs) to validate and refine the key performance factors under investigation. This multi-source convergence allowed the researcher to reconcile discrepancies and obtain a more nuanced understanding of each factor. For instance, the factors related to digital readiness initially presented conflicting interpretations across data sources. The literature review emphasized technical infrastructure and employee IT skill levels as core to digital readiness, whereas expert interviewees highlighted the importance of organizational culture and change-management preparedness, and FGD participants raised concerns about individual willingness to adopt new technologies. Through triangulating these inputs, the study was able to resolve the divergent insights and redefine technological factors in a more holistic manner. The refined definitions encompassed both technological and human dimensions of readiness, aligning the concept with evidence from all three sources. This triangulated resolution not only clarified the construct for subsequent

analysis but also exemplified how drawing on multiple data perspectives helped validate the factor's relevance in Bahrain's public-sector context.

3.6.2 Quantitative Approach

3.6.2.1 Data Collection

Having identified and categorized the key factors influencing employee performance in the Bahraini public sector through expert interviews and focus group discussions, the study quantified and validated these insights with a broader population. This next step involved designing a structured questionnaire to gauge public sector employees' perceptions of each factor's relevance and impact.

In line with established mixed-methods research practices (Creswell and Plano Clark, 2018), the development of the questionnaire was informed by both theoretical frameworks - including Herzberg's Two-Factor Theory, the Job Demands-Resources Model, and Becker's Human Capital Theory - and empirical findings from the prior qualitative stages. Specifically, the final list of factors derived from focus group categorization provided the foundation for constructing clear, thematically organized survey items (Bryman, 2016). The questionnaire was further refined through pilot testing with a small subgroup of public employees to ensure face validity and readability (Saunders et al., 2019).

This sequential integration of qualitative and quantitative methods allowed for a comprehensive and context-sensitive investigation of employee performance factors in Bahrain's public sector. The study ensured that subsequent machine learning analyses would be built on a robust, data-driven framework by moving from exploratory stages, where new themes and categories emerged, to a confirmatory stage involving a larger sample (Patton, 2015). The questionnaire thus represents a natural progression of the research design: it captures the essential variables

identified in earlier phases while providing a systematic means to test their prevalence, strength, and interrelationships across a wider range of public sector contexts (Tashakkori et al., 2020).

The following section outlines the data collection instrument (questionnaire), describing its structure, scales, and administration procedure, followed by a discussion of how the responses were gathered, anonymized, and prepared for statistical and machine-learning analysis.

1. Questionnaire Design and Preliminary Validation

Building on insights from the systematic literature review, expert interviews, and focus group discussions, the researcher developed a structured questionnaire to measure the multifaceted factors influencing employee performance in Bahrain's public sector. This instrument is firmly grounded in both theoretical constructs discussed extensively in the literature review in terms of the nature of their impact on performance, such as Herzberg's Two-Factor Theory and the Job Demands-Resources Model, and empirical evidence derived from the qualitative phases. By aligning each question with one or more categories identified through thematic analysis such as *Individual Capabilities and Competencies*, *Workplace Environment and Support*, and *Motivation and Engagement*, the questionnaire ensures comprehensive coverage of all identified performance drivers (Bakker and Demerouti, 2007; Bryman, 2016).

In constructing the measurement model, careful attention was given to whether each of the 46 performance-related factors should be treated as reflective or formative constructs, based on established measurement theory. Reflective constructs, such as *job satisfaction* and *public service motivation*, were conceptualized as latent variables manifested in their indicators, with intercorrelated items reflecting underlying psychological

states (Jarvis et al., 2003). Conversely, formative constructs, such as *digital literacy*, were defined by their indicators, comprising distinct dimensions that collectively shape the construct, even if they are not highly correlated (Coltman et al., 2008). Adopting this mixed measurement approach ensured that the instrument accurately captured both the psychological and structural components of employee performance. This methodological decision aligns with best practices in scale validation, ensuring that construct specification is matched to the theoretical and empirical properties of the variable being measured. By distinguishing between formative and reflective models where appropriate, the study increased the internal consistency and conceptual clarity of the overall model.

Initially, the questionnaire was presented to five experts who specialize in human resources and academic research methodologies. Their feedback focused on improving the clarity and relevance of the items, evaluating the accuracy of each scale, and aligning item wording with the Bahraini cultural context. At the same time, a language specialist reviewed and refined the questionnaire to confirm its appropriateness in both Arabic and English, ensuring that the final instrument would be accessible to a diverse range of public-sector employees. This process of expert review and linguistic refinement helped eliminate ambiguities, minimize redundancy, and guarantee that the items reflected the theoretical and practical realities of Bahrain's public sector (Fowler, 2014).

Following these refinements, the questionnaire underwent a pilot test involving 25 employees who represented different job levels, functional areas, and ministries within Bahrain's public sector. These pilot participants were asked to complete the survey and provide feedback regarding question clarity, length, and cultural sensitivity. The pilot data were then analyzed to detect any problematic items and assess initial

response distributions for each factor category (Roland et al., 2001). Where necessary, the researcher revised individual items to align more closely with the language and expectations of typical Bahraini public-sector respondents, while also ensuring that the Likert scales adequately captured the breadth and depth of employee attitudes (Dillman et al., 2014).

To evaluate internal consistency, preliminary Cronbach's alpha values were calculated for each multi-item scale, following standard psychometric procedures (Nunnally and Bernstein, 1994). As illustrated in Table 3.1, the resulting alpha coefficients ranged from $\alpha = 0.874$ (for Individual Capabilities and Competencies) to $\alpha = 0.930$ (for Organizational Culture and Governance), indicating high reliability across these key domains. In addition, the aggregate reliability for all 46 variables combined was $\alpha = 0.971$, underscoring the robustness of the questionnaire as a whole. Although slightly lower, the "Overall Performance" scale exhibited an alpha of $\alpha = 0.749$, still within acceptable bounds for early-stage research (DeVellis, 2017; Hair et al., 2022). These coefficients reinforce that the survey items measure their intended constructs consistently, thereby validating the questionnaire's structure prior to large-scale distribution.

Table 3.1: Reliability Analysis Test

Scale	Cronbach's Alpha	No. of Items
Individual Capabilities and Competencies Factors	0.874089	12
Workplace Environment and Support Factors	0.913628	8
Motivation and Engagement Factors	0.878524	8
Organizational Culture and Governance Factors	0.929496	6
Development and Growth Opportunities Factors	0.909882	4
Operational Efficiency and Innovation Factors	0.907290	6
Ethics, Sustainability, and External Factors	0.916364	2
All Variables	0.971208	46
Overall Performance	0.748533	4

Upon integrating all expert recommendations, pilot-test feedback, and reliability results, the final questionnaire, as illustrated in Appendix (D),

emerged as a comprehensive and methodologically sound instrument for investigating the determinants of employee performance in Bahrain's public sector. It contains items that are explicitly mapped to the constructions verified by earlier qualitative findings, ensuring both theoretical coherence and practical relevance. Such a rigorous design process, encompassing expert review, pilot testing, and reliability assessment, lends credibility to the questionnaire and provides a solid empirical foundation for the subsequent phases of data collection, machine-learning analysis, and potential performance enhancement initiatives within Bahraini governmental organizations (Bakker and Demerouti, 2007; Bryman, 2016).

2. Administration and Data Collection

Study Population and Sample

This study draws on a population of approximately 41,000 public sector employees in Bahrain, as the Civil Service Authority reported in January 2024 (Akhbar-Alkhaleej, 2024). In light of Krejcie and Morgan's (1970) guidelines, a minimum sample size of 381 is recommended for a population of this magnitude. Exceeding this figure can enhance the representativeness and robustness of the data (Bryman, 2016; Hair et al., 2022). By securing 391 complete questionnaires, the study surpassed the 381 responses recommended by Krejcie and Morgan (1970). This slight excess further reduces the risk of sampling error and strengthens statistical reliability, particularly if the data are to be subdivided by job category, ministry, or other demographic factors (Hair et al., 2022). The extra buffer also compensates for partial completions or unforeseen nonresponse patterns, thus bolstering the dataset's validity (Bryman, 2016).

Sampling Approach

Recognizing the geographical dispersion and organizational diversity of Bahrain's public sector, the study employed a simple random sampling (SRS) approach within a probability-based framework. Using Morgan's table as a guideline, a random sample of 381 government employees was selected from a total population of 41,000 public sector employees. To ensure randomness, participants were chosen through a computerized random selection process, minimizing potential biases and enhancing the generalizability of the findings (Creswell and Creswell, 2018; Fowler, 2014). This method allowed every public sector employee an equal chance of being included in the study, addressing concerns about representativeness and reducing the risk of selection bias (Dillman et al., 2014). A secure web-based platform (Microsoft Office Forms) was used to distribute the questionnaire to the randomly selected participants.

This approach balanced feasibility, cost-effectiveness, and efficiency while leveraging Bahrain's robust digital infrastructure and the public sector employees' widespread familiarity with online tools (Fowler, 2014). Online surveys also ensured privacy and convenience, allowing respondents to complete them at their own time and location, reducing social desirability biases, and encouraging more honest, thoughtful answers (DeVellis, 2017).

Over a 28-day response window, participants had ample time to review the questions, seek clarifications, and submit their responses. Following ethical research standards, participant anonymity and voluntary participation were strictly upheld. No personally identifiable information was collected, and all responses were treated confidentially (Bryman,

2016). These safeguards were implemented to encourage openness and candour, particularly given the hierarchical structures in public sector employment (Saunders et al., 2019). By employing a randomized selection process, this study ensured a representative sample, enhancing the validity and reliability of the findings.

3.6.2.2 Data Analysis

Machine learning algorithms have become necessary in current data-intensive applications, with efficient processing of complex datasets and insightful predictive analysis facilitated through them.

As seen in Figure 3.4, processing begins with the preparation of data, in which demographic fields not relevant to the current study are removed, and the 2024 performance indicator is retained as the principal output variable. Any additional irrelevant column is removed at this stage to make the feature set simple, such that the dataset only reflects factors directly impacting employee performance. Categorical variables are then converted to machine-readable forms, often through a label or one-hot encoding, so that algorithms can effectively read and utilize such features. To counteract any potential class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) generates synthetic samples of underrepresented classes, thereby strengthening model training dynamics and minimizing bias in prediction.

When data preparation is complete, an initial set of classification algorithms is trained: Gradient Boosting, XGBoost, Random Forest, KNN, and SVM. The first phase provides baseline performance (i.e., accuracy, F1-score) and determines algorithms and hyperparameters with particular potential for optimization. A Genetic Algorithm (GA) is subsequently employed for feature selection and model setting tuning. It starts with a population of candidate solutions, each embodying a distinct feature and

hyperparameter configuration combination. GA evolves towards an optimum feature subset and model settings by iteratively assessing each solution's performance (according to accuracy and F1-score), retaining improved solutions through roulette wheel selection, and applying crossover and mutation operations. High-potential solutions are cached during each generation, so top-performing models are neither lost nor ignored. After the GA is completed, the study selects its highest-performing feature subset and applies the optimized hyperparameters discovered through evolutionary search.

The chosen models are then retrained on this optimized dataset, and a comprehensive evaluation process benchmarks the performance of the enhanced models. By pairing diligent data preparation, knowledge-based feature selection, and evolutionary-based model optimization, this method produces a robust and accurate predictive framework for employee performance. The outcome is an end-to-end solution, based on scientific and practical principles, that delivers actionable insights into the most significant determinants of public-sector workforce outcomes.

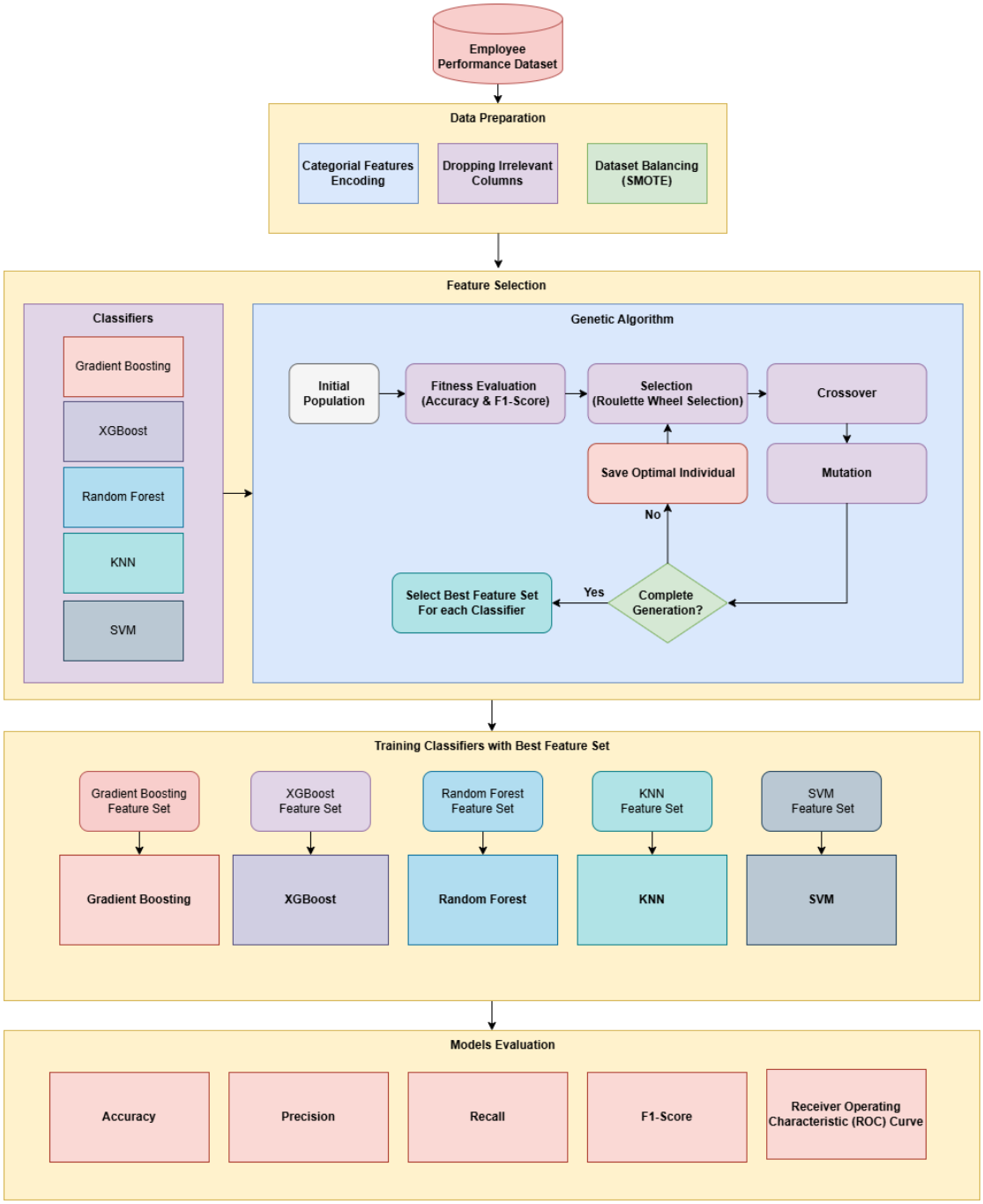


Figure 3.4: Quantitative Research Methodology

1. Data Preparation

Data preparation is widely regarded as a fundamental component of the machine learning pipeline, with the capacity to transform raw data into a standardized, high-quality format that is conducive to model training (Brownlee, 2020; Géron, 2019). By resolving discrepancies systematically,

imputing for missing values, and dealing with noisy observations, researchers enable learning algorithms to reveal actual underlying relationships in a collection of information (Hastie et al., 2009). The removal of irrelevant variables, the encoding of categorical features, the balancing of between-class distributions, and the normalization/scaling of numerical data can form part of such a stage. Implementing these actions has been demonstrated to enhance model performance and facilitate a more profound and precise understanding of the underlying features contributing to prediction (DeVellis, 2017). It is imperative to emphasize that meticulous data preparation is the cornerstone for sound and transparent machine learning, ensuring predictive accuracy and generalizability.

- Categorical Feature Encoding: Converting categorical variables into numerical form is integral because most machine learning algorithms can only handle numerical inputs (Dahouda and Joe, 2021). Label encoding, the process of assigning an integer to each unique category, maintains critical distinctions among categories, facilitating more seamless model training and improved downstream tasks such as feature selection and hyperparameter tuning (Géron, 2019). The label for all non-numeric fields (e.g., departmental names and job titles) was coded by generating a unique integer label for each category. Special care was taken to document the mappings in a reference file, ensuring that future analyses could interpret the encoded data accurately. Also, spot checks were performed to confirm that categories with only a few instances did not inadvertently skew the numeric relationships among features (Hastie et al., 2009).
- Dropping Irrelevant Columns: Eliminating redundant or obsolete variables reduces noise and minimizes the risk of overfitting (Brownlee, 2020). Models that only focus on salient features tend to provide more

consistent insights and do not clutter their decision-making process with unnecessary data (DeVellis, 2017). As such, every column in the dataset was meticulously reviewed, removing fields discovered to be immaterial to the overall objective of predicting employee performance. Columns marked as obsolete or inconsistent with the literature on performance management were removed.

- Dataset Balancing with SMOTE: Imbalanced class distributions can bias machine learning algorithms towards poor predictive performance for minority classes (Géron, 2019). The Synthetic Minority Over-Sampling Technique (SMOTE) is most commonly used to handle imbalanced datasets by synthetically generating new instances of an underrepresented class. Instead of merely replicating existing data points, SMOTE generates synthetic observations by interpolation. Specifically, it takes a minority sample xi and one of its k-nearest neighbors x_{i+1} and then calculates a new point x_{syn} via the following formula:

$$x_{syn} = x_i + r \cdot (x_{i+1} - x_i) \quad (3.1)$$

Where r is a value between 0 and 1 at random, by interpolating between real-data pairs, SMOTE can allow a model to learn about the relational structures in the minority class and, in consequence, to improve performance in imbalanced classification problems without unfairly inflating noise (Brownlee, 2020).

After verifying that some minority classes were extremely underrepresented in the dataset, the SMOTE was used to generate more synthetic observations for those classes. Careful k-neighbors and oversampling ratio tuning were done to preserve the dataset's essential features with an increase in each class's representation. Model performance was tracked throughout over a validation subset to ensure

that oversampling did not result in overfitting and artefact trends. Furthermore, recorded logs of SMOTE's parameters and the rationale for parameter selection were maintained. All of these were done in a bid to successfully balance class distributions and uphold the degree of methodological transparency for reproduction and future testing.

Data preparation techniques - feature encoding, irrelevant feature deletion, and balancing datasets - play a key role in model dependability and real-world usability (DeVellis, 2017; Hair et al., 2022). By smoothing out structures in data and eradicating confounds, researchers effectively mitigate the risk of bias and spurious findings. In addition, utilizing transparent processes, complete with documentation and justification, encourages reproducibility, a hallmark of scientific investigation (Tashakkori et al., 2020). Ultimately, a practical data preparation stage encourages machine learning performance and brings stakeholders transparency, allowing them to have confidence and act in confidence concerning insights generated through predictive models.

2. Descriptive Statistics

A thorough descriptive analysis of demographic factors offers valuable insights into the composition of a workforce and the broader organizational context in which employees operate (Bryman, 2016). Although the current study employed a simple random sampling strategy, several measures were taken to include diverse roles and various government sectors, thus enhancing the likelihood that our sample reflects aspects of the actual employee distribution across ministries (Fowler, 2014; Saunders et al., 2019). Specifically, the researcher aimed to reach participants occupying different job titles, tenure levels, and educational backgrounds, an approach commonly recommended to mitigate inherent biases in convenience samples (Etikan et al., 2016).

Understanding demographic variables such as age, gender, educational attainment, and years of service is crucial for at least two reasons. First, these characteristics often shape organizational outcomes, including employee engagement, performance, and retention (Rowley, 2004). Second, exploring the distribution of these traits provides a contextual anchor for interpreting subsequent findings, such as performance metrics and specialized roles within the public sector (Al-Khalifa and Aspinwall, 2001; Etikan et al., 2016). Consequently, the descriptive results that follow shed light on the professional diversity and experience levels within Bahrain's ministries, offering a snapshot of the institutional reality that informs policy decisions and workforce planning (Bahrain Economic Development Board, 2021). By identifying key demographic patterns, policymakers and HR leaders can better tailor employee development initiatives, promotional pathways, and training programs to the needs of a multifaceted public sector.

The sections below will detail the demographic patterns observed, highlighting the balance of gender representation, age structure, educational qualifications, job titles, and years of service among the respondents. Such granularity not only showcases the depth of the sample, albeit drawn through simple random means, but also reinforces the practical relevance of these descriptive findings for guiding evidence-based interventions (World Bank, 2021).

- Gender Distribution: The dataset shows a relatively balanced distribution between male (192) and female (199) workers, an almost even split in the sample under consideration. That observation closely corresponds with current statistics from Bahrain's Social Insurance Authority (ALAYAM, 2022), reporting female workers at 53.2% of Bahrain's public sector workforce through 2022. As such, a near-equal split signifies an improvement in female empowerment and gender diversity in government positions; it signifies Bahrain's overall objectives for workforce diversity (Bahrain Economic Development Board, 2021). In practice, studies have posed that balanced male-female workforces can infuse new thinking into policymaking and service delivery (Eagly and Carli, 2003). In that regard, such trends can contribute positively towards Bahrain's drive to modernize and consolidate its public institutions.

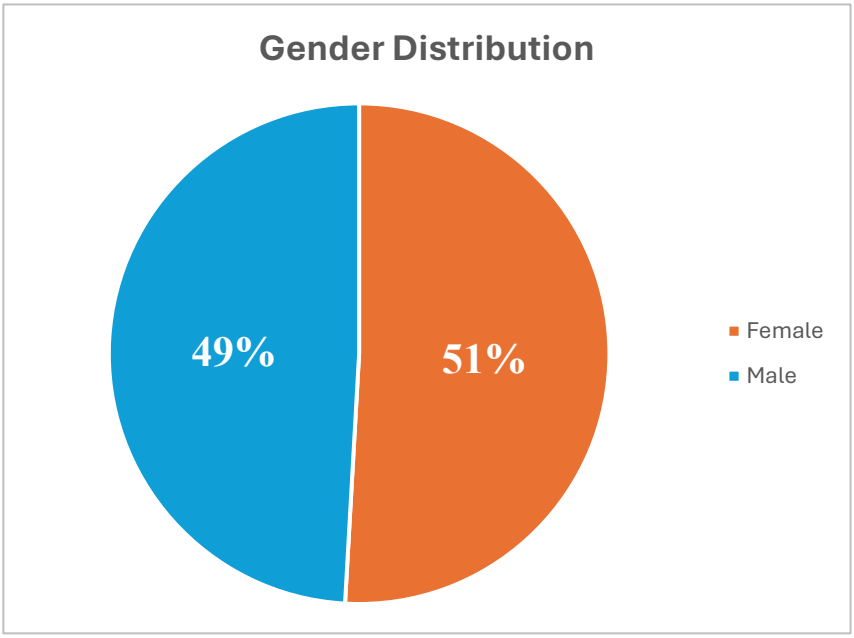


Figure 3.5: Gender Distribution

- Age Structure: In terms of age, the largest clusters are found in the 25–34 (145 employees) and 35–44 (122 employees) ranges. This majority of mid-career professionals aligns with the notion that the Bahraini public sector actively invests in retaining talent during employees' peak productivity years (International Labour Organization, 2020). Meanwhile, smaller cohorts in the 24-and-under (29) and 45–54 (64) ranges point to a balance between new entrants who bring fresh perspectives and seasoned staff who provide institutional memory. The 55–64 (28) and 65-or-above (2) groups remain limited, which may reflect transition planning for impending retirements or higher-level consultative roles at these ages (OECD, 2015).

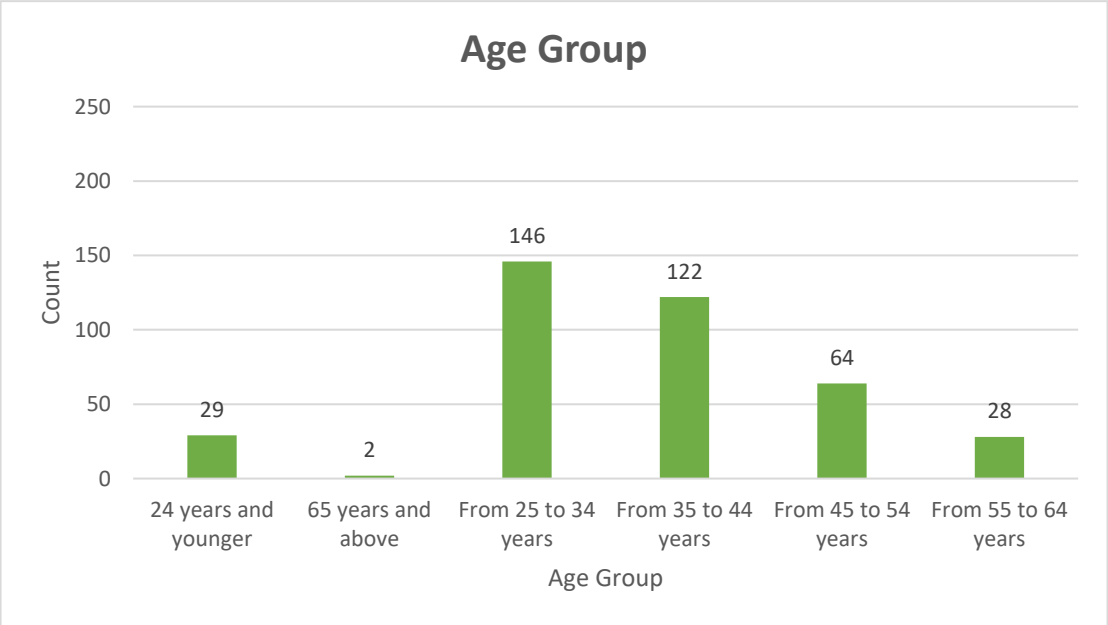


Figure 3.6: Age Group

- Educational Qualifications: The workforce profile shows a strong focus on higher education: 292 individuals have Bachelor's degrees, 49 hold Master's degrees, 35 possess High School/Diploma qualifications, and 15 are Doctorate holders. This distribution indicates that Bahrain's public sector values formal education in its hiring and advancement strategies, likely to address the growing need for specialized knowledge and technical skills (UNESCO, 2016). Moreover, this high

educational standard can enhance adaptive capacity, as employees with solid educational backgrounds are generally more receptive to upskilling and embracing innovative practices (World Bank, 2021).

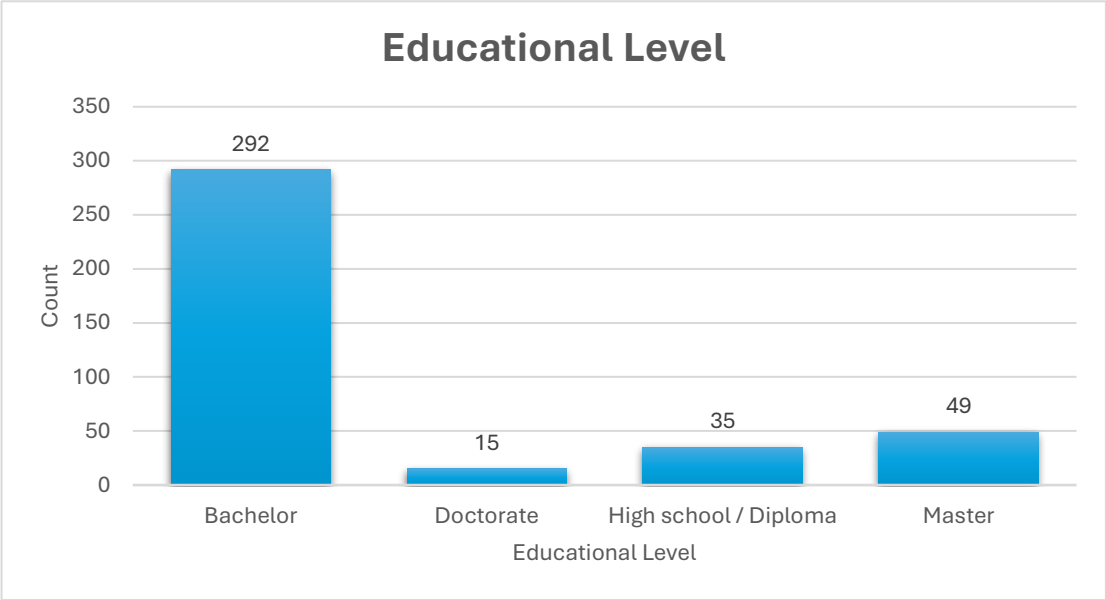


Figure 3.7: Educational Level

- Job Title Distribution: A large number (272) are employed at the Senior Specialist/Specialist level, highlighting the importance attached to government work on detailed expertise in policy analysis, IT, and project management, among other areas. There are 71 Chiefs/Team Leaders, highlighting intermediate supervision to oversee efficient specialist groups (Al-Khalifa and Aspinwall, 2001). Administrative Technicians (32) span key supporting functions, and 13 General Managers/Managers span strategic management positions that guide departmental-level policy implementation. Only three are at the Undersecretary/CEO level, highlighting a top-heavy structure with high-level decision-making tending to get concentrated (Abdulla and Shaw, 1999).

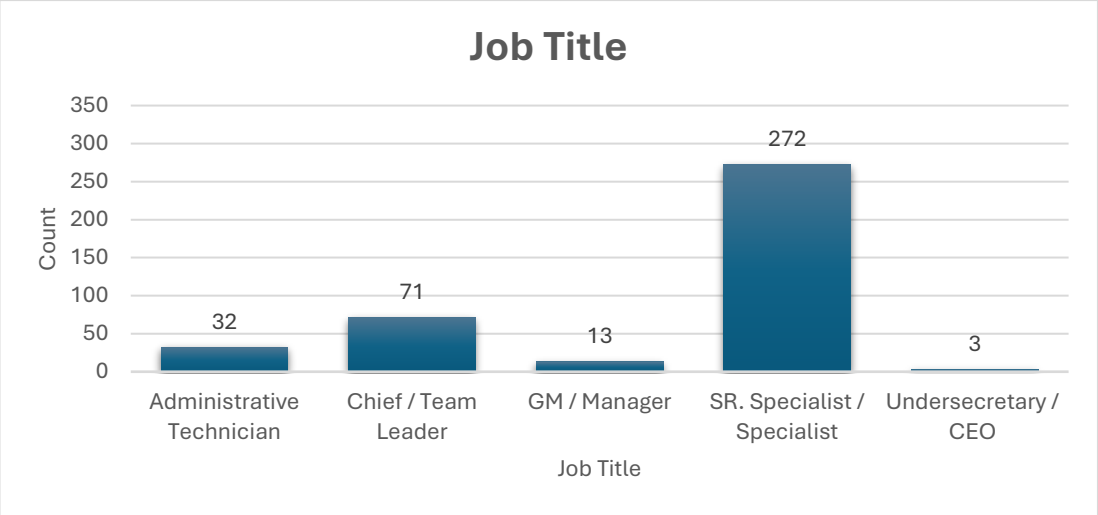


Figure 3.8: Job Title

- Years of Service: Tenure data reveals that 11–15 years of experience (105 employees) are most common, suggesting a substantial mid-to-senior talent pool with broad exposure to governmental processes. Another 82 employees have been in the sector for more than 20 years, underscoring the presence of longstanding institutional memory that can support mentorship and continuity of best practices (Rowley and Slack, 2004). Interestingly, the same number (82) have served less than 5 years, indicating a considerable influx of newer employees, potentially from increased recruitment drives or shifting workforce strategies. The remaining categories, 5–10 (71 employees) and 16–20 (51 employees), further confirm the diverse range of experience levels contributing to public administration in Bahrain (GCC Statistical Center, 2019).

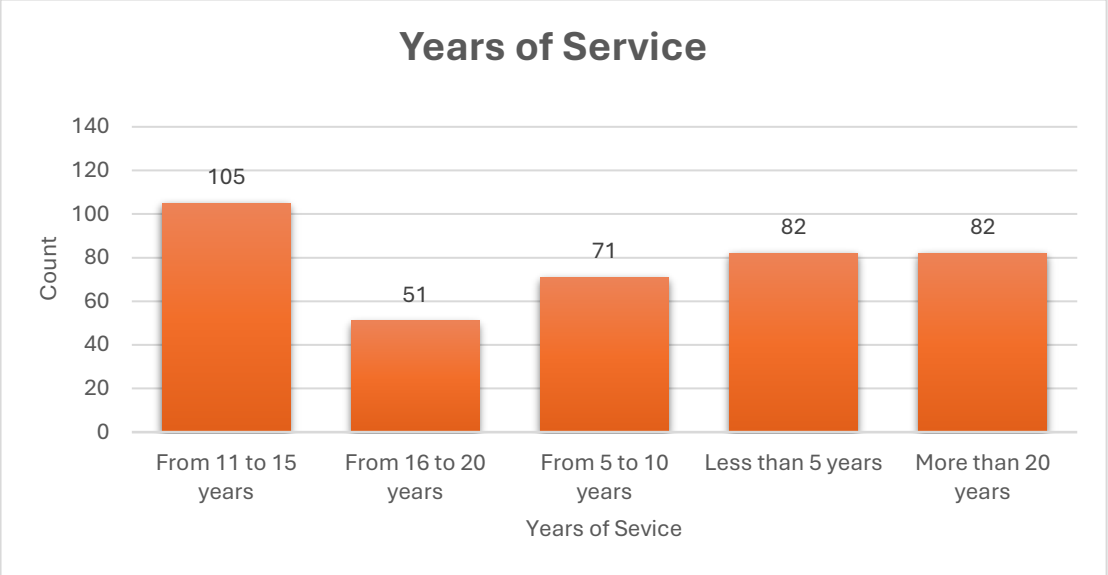


Figure 3.9: Years of Service

- Performance Trends: Regarding performance, 227 employees fully meet expectations, 82 exceed expectations, and 51 far exceed expectations. This shows that most of the public sector workforce is performing at or above the standard, due to strategic HR investments in performance management and skills development (Al-Haddad and Kotnour, 2015). However, 26 employees only partially meet expectations, and 5 require improvement, highlighting a small gap that needs targeted training or a more advanced appraisal system. These figures demonstrate the overall success of the Bahraini public sector in aligning employee competencies with evolving job demands and indicate areas in which developmental efforts could further enhance workforce effectiveness.

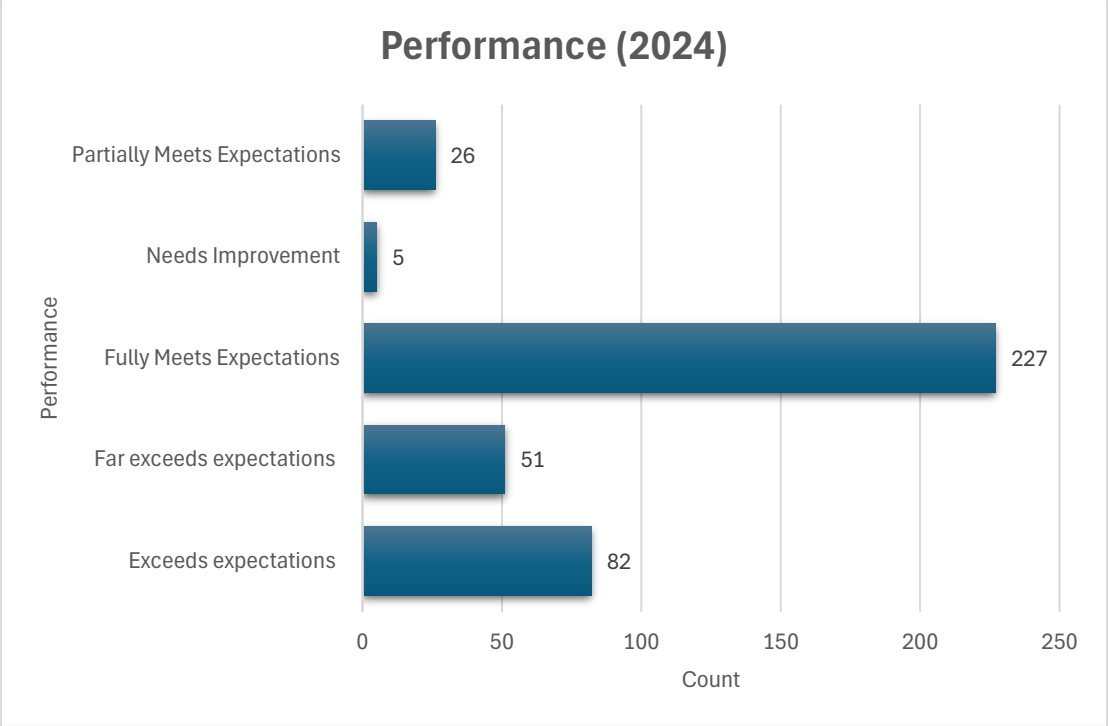


Figure 3.10: Employee Performance Indicators

- Distribution by Government Sector: The sectoral distribution of the research sample depicts a representative distribution of Bahrain's public sector workers in general but more so in education and healthcare that account for more than 60% of civil servants. There is low representation in some of these sectors despite the general sample cutting across a wide range of governmental jobs to make the set of figures adequate for comparing employees' performance across ministries. Overall inclusion across all these sectors ensures that results from research would have implications to guide how to make Bahrain's public sector more effective in employment and more pleasing in jobs.

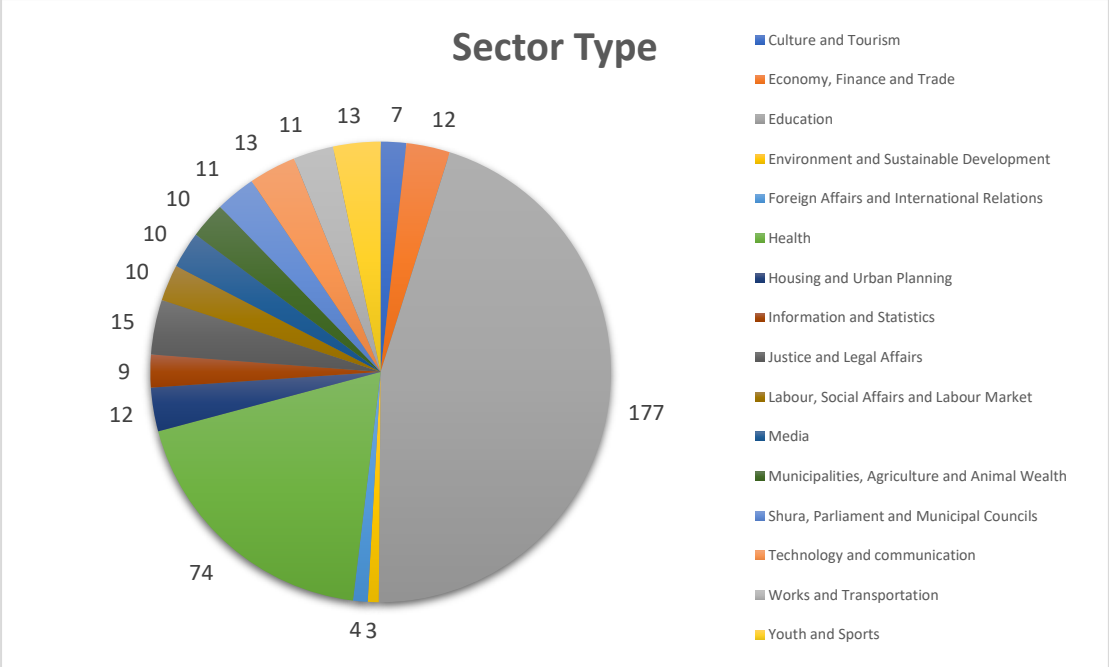


Figure 3.11: Sector Distribution

Overall, the demographic and performance data reflect a well-educated and specialized public sector workforce, balanced by a broad spectrum of experience levels and a strong representation of both genders. These features mirror Bahrain's ongoing drive to modernize its governmental infrastructure, adopt merit-based HR practices, and cultivate a culture of performance excellence (Bahrain Economic Vision 2030). By acknowledging these patterns, spanning age, education, tenure, job roles, and performance outcomes, policymakers and HR leaders are better positioned to refine recruitment, optimize professional development, and reinforce employee engagement throughout the public sector.

3. Feature selection using a Genetic Algorithm

Applying feature selection in the construction of predictive models offers three principal advantages. Primarily, it facilitates a more comprehensive model comprehension and enhances its interpretability. Secondly, it reduces the time required for model training on the dataset, thereby enhancing efficiency. Finally, it enhances the model's capacity for

generalization by reducing the phenomenon of overfitting, which in turn improves performance on new, unseen data. This approach is widely employed in pattern classification, feature integration, and enhancing predictive model performance (Rastogi et al., 2023; Tubishat et al., 2020; Zhang et al., 2020). Nevertheless, assessing all potential subsets is often a costly endeavour. Therefore, it is necessary to seek a computationally feasible and qualitatively sensible solution.

As discussed in the literature review and to fill this gap caused by poor traditional feature selection, a robust alternative involves evolutionary algorithms, including Genetic Algorithms (GAs) proposed by Holland (1992), which iteratively refine solutions through five phases: initialization, fitness assignment, selection, crossover and mutation, thus identifying subsets of features that enhance model accuracy and interpretability (Ali and Saeed, 2023; Ghatasheh et al., 2022; Vijayanand and Devaraj, 2020). GA-based methods are effective in a variety of optimization scenarios; however, their application in the field of HR analytics, particularly in the context of employee performance prediction, remains underutilized. Prior research often stops short of benchmarking multiple classifiers under a GA-based FS framework. Furthermore, studies that do apply GAs sometimes lack a systematic comparison against filter or embedded methods, leaving open the question of how best to combine GAs with leading machine learning (ML) algorithms (e.g. gradient boosting, XGBoost, random forest, support vector machines, k-nearest neighbours) to address the unique challenges of employee performance management (EPM), an area this study aims to advance.

A Genetic Algorithm draws inspiration from Darwinian evolution, with processes like reproduction, mutation, and survival of the fittest. Any candidate solution is encoded in the shape of an individual, most typically

in a chromosome structure. In feature selection, a chromosome is most usually encoded in a binary structure, with every gene indicating a feature (1 for inclusion, 0 for exclusion of a feature). Through iterative selection, combination, and modification, a population of chromosomes moves towards determining ever more ideal feature subsets. The operation of GAs can be summarized as follows:

i. Initialization:

A population of candidate solutions is initialized. These solutions, or chromosomes, can be represented in binary, real-valued, or other appropriate encoding schemes. The initial population $P(0)$ may be generated randomly or derived using domain-specific heuristics.

- Random Initialization**:**

  Each bit $x_{ij}^{(0)}$ in the initial population is generated from a Bernoulli distribution with parameter p i.e.,

  $$x_{ij}^{(0)} \sim Bernoulli(p) \qquad (3.2)$$

  Where p is the probability of including a feature j in individual j in the individual i at generation 0.

- Heuristic Initialization**:**

  Rather than starting at an entirely arbitrary position, information about a domain can direct starting chromosomes towards potentially useful regions in search space.

ii. Fitness Evaluation:

A fitness function measures the quality of a given feature subset. Common fitness metrics include classification accuracy, precision, recall, or other predictive performance measures obtained via a chosen machine learning model. To mitigate overfitting and encourage parsimony, a regularization term or a penalty for the number of features selected is often incorporated into the fitness function.

Suppose $Perf(x_i)$ is a predictive performance metric (e.g., accuracy, F1-score) of a model trained using only the features selected by x_i. Often, a penalty term is added to discourage selecting too many features. A common formulation of the fitness function is:

$$\text{Fitness } (\boldsymbol{x}_i) = \alpha \times Perf(\boldsymbol{x}_i) - \beta \times \|\boldsymbol{x}_i\|_1 \qquad (3.3)$$

Where:

- $\alpha(\alpha > 0)$ is a weight that scales the importance of the performance metric.
- $\beta(\beta > 0)$ is a weight that scales the penalty for including more features.
- $\|\mathbf{x}_i\|_1$ is the $L_1 - norm$ of $\mathbf{x}_i$, which counts the number of selected features (i.e., the number of ones in the chromosome).

In this way, a larger β increase the penalty for selecting excessive features, thus promoting parsimony (fewer features), while a larger α prioritizes maximizing model performance.

iii. Selection:

The selection step determines which individuals (from the current generation) will be chosen to reproduce and form the basis of the next generation. One of the most common selection methods is roulette wheel selection (also called fitness-proportional selection), where each individual's probability of selection is proportional to its fitness. Concretely, if $Fitness(x_i) = f_i$, the selection probability of the i-th individual is:

$$p_i = \frac{f_i}{\sum_{k=1}^{N} f_k} \qquad (3.4)$$

Other selection methods include tournament selection, rank-based selection, and stochastic universal sampling, each with different trade-offs in terms of diversity and selection pressure.

iv. Crossover (Recombination):

Once pairs of individuals have been selected, crossover (also referred to as recombination) is applied to produce new offspring that combine genetic material from their parents. For binary-encoded chromosomes of length d, a simple yet common approach is single-point crossover. Let:

$$\boldsymbol{x}_p = [x_{p1}, x_{p2}, \dots, x_{pd}] \tag{3.5}$$

And

$$\boldsymbol{x}_q = [x_{q1}, x_{q2}, \dots, x_{qd}] \tag{3.6}$$

be two-parent solutions. If a crossover point c is chosen randomly such that $1 \leq c < d$, then the offspring are created as follows:

$$\boldsymbol{o}_1 = [x_{p1}, \dots, x_{pc}, x_{q(c+1)}, \dots, x_{qd}] \tag{3.7}$$

$$\boldsymbol{o}_2 = [x_{q1}, \dots, x_{qc}, x_{p(c+1)}, \dots, x_{pd}] \tag{3.8}$$

By exchanging segments of parent chromosomes, the GA can explore new regions of the solution space.

v. Mutation:

While crossover recombines existing genes, mutation introduces fresh variations to maintain population diversity. In binary representation, each bit can be flipped with a small probability p_m.

Formally:

$$x'_{ij} = \begin{cases} 1 - x_{ij}, & \text{with probability } p_m \\ x_{ij}, & \text{with probability } 1 - p_m \end{cases} \tag{3.9}$$

If the chromosome is real-valued, the mutation operator often involves adding a small random value Δ drawn from a suitable distribution (e.g., uniform or Gaussian), such that:

$$x'_{ij} = x_{ij} + \Delta, \Delta \sim \mathcal{U}(-\delta, \delta) \quad (3.10)$$

Where δ is the mutation range.

vi. Replacement:

After crossover and mutation, each offspring's fitness is evaluated. The population for the next generation, $P(t+1)$, s then formed by some replacement strategy. Two common strategies are:

- Generational Replacement: The entire current generation is replaced by the newly formed offspring.
- Elitism: A specified number of the fittest individuals (called "elites") from the current generation automatically survive to the next generation, preventing the loss of top solutions due to stochastic effects.

By preserving highly fit individuals, elitism helps ensure that the GA's performance does not regress in subsequent generations.

Termination:

A Genetic Algorithm proceeds iteratively through the aforementioned steps until a termination criterion is satisfied. Typical stop conditions include:

- Maximum Generations (t_{max}): The algorithm halts when a predefined generation limit is reached.
- Fitness Threshold: The run ends as soon as an individual's fitness surpasses a specified target.
- Stagnation: If no significant improvement is observed after several consecutive generations, the algorithm may be considered converged.

Upon termination, the algorithm typically returns the best-performing individual(s) it has encountered over its run, which in feature-selection contexts corresponds to an (approximately) optimal subset of features.

4. Classification Models

Classification models are machine learning algorithms with the purpose of predicting discrete classes out of a group of input variables and, as such, have a definite utility for measuring employee performance in an organizational setting (Patel et al., 2022). In such a setting, whether an individual works at, even exceeding, a certain level of performance can become a deciding criterion in HR-related actions, such as for career advancement and salary increases, and even in concentrated training programs. Classification models can detect trends not necessarily seen through traditional evaluation processes by processing a range of information regarding an individual's performance, attendance record, job-related performance, feedback rating, and additional performance factors (Sarker et al., 2018).

To conduct a robust analysis of employee performance, five classification algorithms will be utilized in our study: (1) Gradient Boost, (2) XGBoost, (3) Random Forest, (4) K-Nearest Neighbors (KNN), and (5) Support Vector Machine (SVM). All these approaches have individual strengths and tackle data features differently, and therefore, our results become more robust and easier to interpret. For example, tree-based approaches such as Random Forest and Gradient Boost work well with complex, non-linear relationships, and SVM works well in high-dimensional space. XGBoost, renowned for its efficiency and scalability, is particularly well-fitting for big data. KNN can work well when feature space is well-characterized, and computational capabilities allow it. By employing these five algorithms, organizations can obtain multi-faceted insights into employee performance and, in turn, enable more innovative, data-driven workforce development strategies.

I. Gradient Boost Classifier

Gradient Boosting (GB) is a widely used assembling method extensively used in machine learning. It builds a strong predictive model by aggregating multiple weak learners in the guise of shallow decision trees, each of which is individually designed to fix the faults of the previous ensembling process (Friedman, 2001). In the iterative process, GB effectively resists the occurrence of prejudice and is prone to achieving excellent predictive accuracy. XGBoost (Chen and Guestrin, 2016), LightGBM (Ke et al., 2017), and CatBoost (Dorogush et al., 2018) have been popular implementations, and their effectiveness and utility have been demonstrated in scholarly and real-world situations.

Core Principle of Gradient Boosting

The underlying principle of Gradient Boosting is training a sequence of weak models, with each subsequent model aimed at the residual errors of the previous models (Friedman, 2001). It is initiated with a straightforward model (generally a constant predictor or a one-level decision tree) as the initial point. Each subsequent tree is then fitted to the deficiencies of the current ensemble, incrementally enhancing the ultimate estimate. This residual-based correction process is at the heart of how GB can incrementally reduce the bias.

Hyperparameter Tuning

Finding the optimal setup for Gradient Boosting usually includes tweaking some significant hyperparameters:

1. Number of Estimators: This refers to the number of boosting iterations. Too few may underfit, and too many may risk overfitting. Methods like cross-validation or early stopping can determine a reasonable trade-off.

2. Maximum Tree Depth: More complex models can detect patterns and remember the training noise. Regulating depth is a simple method of regularization.
3. Minimum number of samples per leaf: Specifies the number of samples required in a leaf. Greater thresholds enable more general, less specific splits, which can be beneficial for generalization.
4. Sampling Methods: Some implementations support subsampling the rows or the features at every iteration, adding randomization that mitigates the risk of overfitting as well as improving model resilience.

By carefully tuning these hyperparameters, practitioners can tailor Gradient Boosting to different performance and resource requirements (Friedman, 2002).

Gradient Boosting's iterative, error-driven process makes it the first choice for many predictive model tasks. Its use of multiple loss functions with exact control of model complexity makes for a forceful system for attacking regression as well as classification tasks (Natekin and Knoll, 2013). By clever selection of the number of estimators, the learning rate, the depth of the trees, and other parameters, Gradient Boosting returns highly generalized solutions reliably (Emami and Martínez-Muñoz, 2023)As seen through popular implementations like XGBoost, LightGBM, and CatBoost, the method is highly relevant in research and business, where accuracy is the number one priority.

II. XGBoost Classifier

XGBoost, short for eXtreme Gradient Boosting, is a powerful machine learning library and algorithm based on gradient boosting decision trees. Introduced by Tianqi Chen and Carlos Guestrin, XGBoost quickly gained popularity in data science competitions and real-world applications due to its superior speed, scalability, and overall performance on both structured

and semi-structured data. Much like other gradient boosting methods, XGBoost sequentially learns weak learners (decision trees in most cases), and iteratively refines the ensemble by focusing on the errors made by the previous models (Chen and Guestrin, 2016; Zhang et al., 2018).

XGBoost's Core Innovations

XGBoost is built on top of standard gradient boosting principles but introduces several optimizations that set it apart:

1. Regularized Objective: A key feature of XGBoost is its regularized objective function. In addition to measuring how well the model fits the data, the objective includes a penalty for model complexity. By penalizing overly complex trees, XGBoost reduces the likelihood of overfitting and enhances its ability to generalize.
2. Second-Order Gradient Approximation: Unlike standard gradient boosting methods, XGBoost leverages information beyond just the first-order (simple gradient) updates by also considering second-order (curvature) aspects of the loss. This extra information often leads to faster convergence and more refined splits when constructing new decision trees.
3. Approximate Tree Learning: When the dataset is large, searching for the best split over all possible feature thresholds can be computationally expensive. XGBoost uses an approximate algorithm that first discretizes feature values into quantiles and then performs a more efficient split-finding procedure over these candidates' split points. This helps maintain high performance even on large datasets.
4. Weighted Quantile Sketch: In distributed and parallel settings, data often arrives in multiple batches on different machines. XGBoost introduces a specialized data structure called the weighted quantile

sketch, allowing it to handle weighted data effectively and maintain robust approximate splits across distributed environments.

5. Block Structure and Cache Awareness: XGBoost incorporates cache-friendly data structures that optimize memory usage and improve cache locality, speeding up the training process. A “block” of data is constructed in memory such that contiguous memory accesses reduce overhead in gradient boosting iterations.

Training Process and Objective Function

XGBoost’s training process is iterative. It starts with an initial model and progressively adds new decision trees to address the most persistent errors. Unlike some boosting algorithms, XGBoost incorporates a term that penalizes complex models, ensuring that each new tree must both reduce errors and remain sufficiently simple. Over time, the ensemble becomes more accurate, and the algorithm naturally avoids overfitting through its built-in regularization strategies.

By combining a regularized objective, refined gradient updates, approximate techniques for split finding, specialized data structures, and efficient memory use, XGBoost stands out as a leading framework for machine learning tasks (Chen and Guestrin, 2016; Zhang et al., 2018). Its ability to handle large volumes of data, adapt to different contexts, and maintain strong performance underlines its status as a go-to method for practitioners and researchers seeking both speed and accuracy.

III. Random Forest Classifier

A Random Forest is an ensemble learning method that builds multiple decision trees and combines their predictions. By averaging or voting across these individual trees, a Random Forest often delivers robust,

accurate results while limiting the overfitting issues commonly associated with standalone decision trees (Breiman, 2001).

Core Idea of Decision Trees

In a classification context, a decision tree splits the training data based on chosen features and thresholds to form "nodes" that group similar instances.

- Impurity Measures: Common metrics for deciding the best split include Gini impurity and entropy, each quantifying how homogeneous the classes are within a node.
- Greedy Splitting: Each node split is chosen to reduce impurity best, repeatedly partitioning the feature space until leaf nodes predominantly contain examples from a single class.

A single decision tree can grow very deep, often capturing intricate details of the training data. While this may yield low bias, it also risks overfitting, meaning the tree adapts too closely to the training set at the expense of general performance on unseen data.

Bagging Ensemble Principle

To address overfitting, Random Forest employs bootstrap aggregating (bagging).

- Bootstrapping: The algorithm creates multiple new training datasets (each called a bootstrap sample) by randomly drawing samples with replacements from the original data. Each tree is trained on a different bootstrap sample.
- Aggregating Predictions: By combining (averaging or voting) the predictions from many slightly different trees, the Random Forest smooths out individual errors and variance, making the overall model more stable.

Notably, each bootstrap sample typically contains most - but not all - of the training instances. Those left out are called out-of-bag (OOB) samples and can be used as a convenient estimate of model performance without requiring a separate validation set. A Random Forest combines decision trees through bootstrapping and feature subsampling to produce a robust, highly accurate model. Averaging the output from numerous diverse trees mitigates the overfitting problem characteristic of single, fully grown trees. The resulting ensemble is known for its strong predictive performance, relative ease of implementation, and capacity to handle high-dimensional data. As such, Random Forests have become a standard tool for classification and regression tasks in a wide variety of domains (Breiman, 2001).

IV. K-Nearest Neighbors (KNN) Classifier

The k-Nearest Neighbors (KNN) algorithm is one of the most intuitive and straightforward forms of supervised learning, and was first touted by Cover and Hart (1967). KNN is a lazy learner that waits until the inference stage to conduct any computation. Lacking a training routine in a specific form distinguishes it from most algorithms, which derive a model (e.g., coefficients for a model, a decision boundary, etc.) in an explicit training phase (Abu Amra and Maghari, 2017). KNN has been applied in numerous fields including pattern recognition, recommendation, bioinformatics, and computer vision. It is regarded as useful for the following:

- Simplicity: The "nearest neighbor" principle of "locate your neighbors and use them to make a decision" is simple in its premise.
- Adaptability: KNN can be paired with any weighting scheme and any distance measure and hence can be adaptable in heterogeneous data environments.

- Competitive Performance: On conditioned data (with proper feature scaling and dimensions taken into consideration), KNN can deliver classification and regression accuracy at a level similar to complex models.

Distance Metrics and Decision Rule

Central to KNN's approach is the concept of "closeness" or distance between the query instance and points in the training set. Common distance metrics include Euclidean, Manhattan, or more specialized approaches for text or high-dimensional data.

- Decision Rule: Once the nearest neighbors are identified, their labels (for classification) or numerical values (for regression) are used to produce the final prediction.
- Weighted Voting and Tie-Breaking

In many cases, KNN assigns a larger influence to neighbors that are closer to the query point. For classification, this may involve giving those closer points greater voting power; for regression, a distance-weighted average is frequently used. If multiple classes tie in votes, implementations may choose randomly among them or adopt a consistent rule (e.g., favoring the smallest label).

Role of k

The parameter k determines how many neighbors are taken into account during prediction:

- Small k: This may lead to overfitting, as too few neighbors can make the model overly sensitive to noise or outliers.
- Large k: Risks oversimplifying the decision boundary or regression function, potentially obscuring local patterns within the data.

In practice, cross-validation is typically employed to identify the most suitable k, balancing model bias and variance.

k-Nearest Neighbors stands out for its direct, intuitive framework and versatility across various data domains (Abu Amra and Maghari, 2017; Cover and Hart, 1967). By deferring computations until a query point is presented, KNN offers a transparent decision mechanism that can be finely tuned by choosing a distance metric, weighting scheme, and number of neighbors. This combination of simplicity, adaptability, and competitive performance ensures KNN's ongoing popularity in academic research and real-world applications.

V. Support Vector Machine (SVM) Classifier

Support Vector Machines (SVMs) are a family of supervised classification and regression algorithms with origins in research in the 1990s involving Vladimir Vapnik and others. SVMs have emerged as a workhorse in machine learning with a fundamental goal of discovering a hyperplane with a maximal margin between classes, with good generalization in such a way that not only will it accommodate training data but will also make accurate predictions using new unseen data (Cortes and Vapnik, 1995; Fallucchi et al., 2020).

Margin and Support Vectors

In SVM, the margin indicates the distance between the decision boundary and the closest training examples from either class. These closest data points are called support vectors and play a critical role in determining SVM's final decision boundary. By explicitly maximizing the distance to these support vectors, SVMs seek to reduce overfitting and enhance predictive performance.

Hard-Margin and Soft-Margin SVMs

- Hard-Margin SVM: In scenarios where classes are perfectly separable, the SVM formulation enforces that each training example be placed correctly on either side of the margin, prohibiting any misclassifications. While elegant in theory, this strict approach can be overly restrictive, as real-world data often contains overlapping classes or noisy observations.
- Soft-Margin SVM: To accommodate more realistic data, soft-margin SVMs introduce a penalty parameter (C) and slack variables to permit limited violations of the perfect-separation criterion. A large C heavily penalizes misclassifications, emphasizing accuracy but potentially increasing overfitting, while a smaller C allows more tolerance and thus may yield a smoother decision boundary.

The Kernel Trick

In many practical contexts, data are not linearly separable. The kernel trick addresses this issue by mapping the original feature space into a higher-dimensional representation via a kernel function, without requiring explicit computation of new features. Popular kernel types include:

- Polynomial Kernels, which capture interactions between features.
- Radial Basis Function (RBF) Kernels, often effective for a broad range of data distributions.
- Sigmoid Kernels, reminiscent of neural network activation functions.

By substituting dot products with kernel evaluations, the SVM can learn non-linear boundaries that separate complex data distributions, thereby extending its flexibility and robustness.

Overall, Support Vector Machines leverage geometric principles, namely margin maximization, and modern computational strategies such as kernel methods, to deliver strong performance across a wide spectrum of classification and regression tasks (Cortes and Vapnik, 1995; Fallucchi et al., 2020). By elegantly balancing margin size, penalizing misclassifications, and leveraging kernel transformations, SVMs provide a versatile framework capable of addressing both simple and highly complex data structures in contemporary machine learning research and practice. The appendix (E) includes a detailed mathematical explanation of the step-by-step process of training classification models involving a set of algorithms.

5. Features Interpretability Techniques

Interpreting the outcomes of employee performance predictive models is crucial for decision-makers who rely on clear and actionable insights to enhance organizational effectiveness. This section addresses feature interpretability by presenting techniques that clarify the role and influence of individual features within the Decision Tree model utilized in this research. Figure 3.12 illustrates the interpretability techniques adopted, emphasizing the importance of both Feature Importance Analysis and SHAP (SHapley Additive exPlanations).

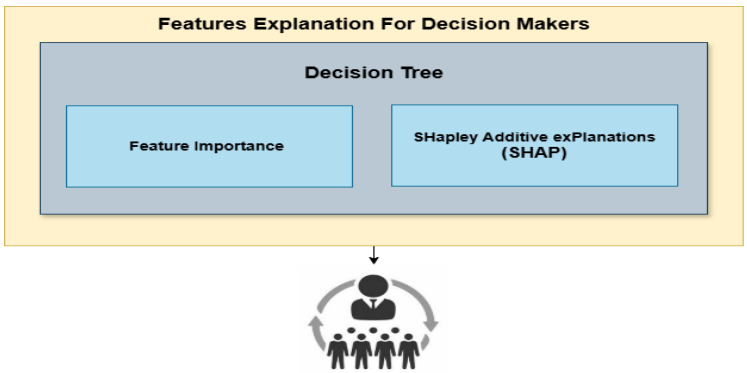


Figure 3.12: Interpretability Techniques

i. Feature Importance Analysis

Feature importance analysis identifies the extent to which every input feature is responsible for a model's predictive power. In essence, it is a measurement of the contribution of individual features to improving a model's precision, thereby determining the most impactful features in determining a model's results. This process finds primary application in tree-based models, including Random Forest and XGBoost, given that such models inherently estimate feature importance in terms of each feature's impurity or error reduction when doing a split (Wu et al., 2023). However, it is important to note that this process is not exclusive to tree-based models; it is also applicable to linear models, where coefficients serve as a surrogate for feature importance, albeit through different mechanisms (Pudjihartono et al., 2022).

The primary strength of feature importance analysis lies in its capacity to enhance interpretability. It provides a comprehensive overview of which features have the most significant impact on prediction without the need to delve into the intricacies of each prediction process. This global perspective enables practitioners and researchers to understand better and articulate the forces that govern model behaviour. This knowledge is of great importance in cases where transparency and explainability are required, such as in healthcare analytics, finance, or any application that must know how predictive decisions are being formulated (Pudjihartono et al., 2022; Wu et al., 2023). Furthermore, results of feature importance can be displayed graphically in terms of bar plots, heatmaps, or other graphical representations, making it easy to display complex relationships. Consequently, feature importance analysis is a compelling model improvement and assessment step.

ii. SHAP (SHapley Additive Explanations)

SHAP (SHapley Additive Explanations) is a model interpretability framework based on Shapley values, a fundamental concept in cooperative game theory. Introduced by Lundberg and Lee (2017), SHAP provides a unified measure to quantify the contribution of each feature to a model's prediction by considering all possible feature combinations. This approach ensures local accuracy, consistency, and fair attribution of feature importance across different types of machine learning models. SHAP has been widely adopted in research and industry due to its rigorous theoretical foundation and practical implementations, such as the TreeExplainer, which significantly improves computational efficiency for tree-based models (Lundberg et al., 2018).

Theoretical Foundations of SHAP

1. Shapley Values in Game Theory

The SHAP framework is built upon Shapley values, which originates from cooperative game theory (Shapley, 1953). In this context:

- Each feature in a dataset is treated as a player in a cooperative game.
- The predictive model acts as the game, where the objective is to distribute the total prediction fairly among the features.
- The contribution of each feature is determined by considering all possible subsets of features and how the prediction changes when a feature is included or excluded.

The Shapley value ϕ_i for a feature i is calculated as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \qquad (3.11)$$

- N is the set of all features.
- S is a subset of features excluding i
- $f(S)$ represents the model's prediction using only features in S.

- $f(S \cup \{i\})$represents the model's prediction when feature i is added to S.
- The factorial weighting term ensures a fair distribution of contributions across all possible coalitions.

This formula guarantees that feature contributions are fairly distributed, making Shapley values a theoretically sound method for feature attribution.

2. Properties of SHAP Values

SHAP values satisfy several important properties as stated Lundberg and Lee (2017):

- Local Accuracy: The sum of the SHAP values for all features in a given instance equals the model's output for that instance.

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i \quad (3.12)$$

Where ϕ_0 represents the base prediction (e.g., the mean prediction over all data points).

- Consistency: If a model is modified such that a feature contributes more to predictions, its SHAP value will not decrease.
- Additivity: The SHAP values of individual features add up to the total model prediction, ensuring interpretability.

3. Computational Challenges and SHAP Approximations:

Since the exact computation of Shapley values requires evaluating all possible feature subsets (exponential complexity $O(2^N)$) SHAP provides optimized methods for different model types.

Model-Agnostic Approach: Kernel SHAP

Kernel SHAP is a sampling-based method that approximates Shapley values for any model by treating it as a black box. It estimates feature contributions using Monte Carlo sampling but can be computationally expensive for large datasets (Lundberg and Lee, 2017).

4. Model-Specific Optimizations
    - TreeExplainer (for Decision Trees, Random Forests, and Gradient Boosting Trees): This method efficiently computes exact SHAP values by leveraging the tree structure (Lundberg et al., 2018).
    - DeepExplainer (for Neural Networks): An approximation based on expected gradients to compute SHAP values efficiently in deep learning models (Singh et al., 2020).
    - LinearExplainer (for Linear Models): Uses classical feature attribution methods, making it computationally efficient.

iii. Rationale for Using a Decision Tree with SHAP

In this study, it was determined that a Decision Tree Classifier offered an optimal balance between interpretability, efficiency, and suitability for multi-class classification. Firstly, decision trees are inherently transparent: each node and branch in the tree's hierarchical structure corresponds to an easily understood, rule-based split of the data. This clarity is advantageous when communicating model logic to both academic and practitioner audiences, as stakeholders can trace the flow of decisions step by step. Secondly, the SHAP TreeExplainer has been developed for the purpose of leveraging the internal format of tree-based models, thereby enabling the fast and exact computation of Shapley values. This computational efficiency is especially valuable in a multi-class setting (e.g. distinguishing five distinct performance categories), where the volume of instance-level explanations could become quite large. Conversely, although Support Vector Machines (SVMs) have been shown to outperform other methods in certain contexts, their explanations generally require a model-agnostic mechanism like KernelExplainer, which is more computationally intensive and less attuned to the unique architecture of SVM. Consequently, the selection of a Decision Tree as the primary model not only preserves a high

level of interpretability but also integrates seamlessly with SHAP to produce precise, class-specific insights into how each feature shifts the predictive outcome. This, in turn, allows for the refinement of our understanding of employee performance drivers and supports more informed managerial decision-making.

3.7 Summary

This chapter delineated the research approach used to examine employee performance management in Bahrain's public sector. The study uses a sequential exploratory mixed-methods design that combines qualitative and quantitative approaches to provide richness and credibility. To maintain consistency, the approach is structured using the Research Onion approach (Saunders et al., 2019), which aligns philosophical standpoints, research approaches, and data-gathering methods. The study adopts an objectivist and realist epistemology, assuming that performance drivers, such as job competencies, leadership, and organizational culture, are independent of perception and can be systematically measured. The qualitative phase employs an inductive approach, utilizing systematic literature review, expert interviews, and focus group discussions (FGDs) to identify key performance drivers. These qualitative results guide the deductive phase, where quantitative approaches verify and generalize the findings.

In the qualitative phase, purposive sampling was employed to conduct 22 expert interviews to generate sector-specific knowledge, and interview observations were elaborated in FGDs of 23 government staff and retired government staff. In these groups, factors were categorized in thematically grouped clusters in accordance with theories of human behaviour. The quantitative phase involved a questionnaire that was formulated using theoretical models and qualitative results. The questionnaire was

administered to 391 public sector employees who were randomly selected, exceeding the recommended sample size of 41,000 according to Krejcie and Morgan's (1970) standards. The questionnaire was pilot tested for reliability, which was confirmed using Cronbach's alpha coefficients, ranging from 0.874 to 0.971.

The modelling of the data was undertaken using machine learning models such as Decision Trees, Gradient Boosting, XGBoost, Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). The features were optimized using a Genetic Algorithm (GA) to employ the most valuable predictors. Feature engineering, dataset balancing (with SMOTE), and categorical encoding were employed to improve model precision.

To interpret the results of the models, SHAP (Shapley Additive Explanations) was used to identify the most impactful drivers of employee performance. Decision Trees provided interpretability, sorting key predictors and their hierarchical importance in the measurement of performance. By integrating predictive models based on AI with qualitative and quantitative approaches, this work presents empirical evidence to guide employee performance management in Bahrain's government sector.

Chapter 4
Experimental Evaluation

4.1 Overview

The effectiveness of any prediction model is dependent on a strict process of evaluation that ensures its precision, credibility, and usability in actual applications. The current chapter presents a detailed experimental analysis of the employee performance prediction model, detailing the dataset preparation, preprocessing procedures, identification of models, and performance measurement. The work follows a structured and data-oriented approach to preprocess the dataset, select optimal features, and apply advanced machine learning techniques to enhance predictive performance.

The experimental procedure begins with the formation of a well-delineated dataset, developed based on questions in a survey that capture organizational dynamics, relevant employee characteristics, and metrics of performance. Cleaning, encoding, and SMOTE-based balancing preprocessing techniques are employed to ensure maximum data quality. Feature selection is carried out using a genetic algorithm (GA), such that only the most relevant variables are utilized in the predictive model, making it more efficient and reducing computational load. The study compares five machine learning models, i.e., XGBoost, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), that are systematically tuned using grid search to find their optimal hyperparameters. The performance of models is evaluated using a set of various classification metrics such as accuracy, precision, recall, F1-score, and AUC-ROC curves to give a solid and credible measurement. In order to provide better interpretability, a Decision Tree

Classifier using SHAP values is employed, providing a view of the most impactful variables that affect employee performance.

4.2 Employee Performance Dataset

Developing the Employee Performance dataset played an essential role in our experimental pipeline. It began with raw survey feedback collecting to detect markers of behaviour and demographics of employees in governmental organizations. Initially, the dataset comprised 391 observations in (28) days with an average response time of (8.58) minutes. Python programming language and the Pandas data frame were used to load survey information. Various cleaning processes, such as deleting valueless rows and unfirming answer structures, were conducted on it. Besides, a LabelEncoder was used to convert categorical values (e.g., Level of education, Position title, Gender) to numerical codes, which played a critical role in the pipeline for machine learning.

As a result of comprehensive preparation, the dataset was methodically arranged to retain key features, including personal attributes (e.g., Gender, Age group, Years of experience), individual capabilities factors (e.g., Public Service Motivation (PSM), Emotional Intelligence (EI), Knowledge-Sharing Ability), workplace factors (e.g., Team Dynamics, Leadership Style, Organizational Culture, Work-Life Balance), motivation factors (e.g., Job satisfaction, Employee Engagement, Employee Autonomy), organizational culture factors (e.g., Leadership Style, Diversity and Inclusion, Organizational Transparency) and so on. The survey responses for Performance (2024), Performance (2023), and Performance (2022), alongside Goal Achievement (2024), were incorporated as vital performance indicators. Columns deemed irrelevant or redundant were removed, leaving a coherent feature set for downstream modeling.

Within these features, attributes such as Public Service Motivation (PSM) and Knowledge-Sharing Ability were central in analyzing how intrinsic motivators might correlate with performance outcomes. At the same time, leadership style and organizational culture provide a lens through which to examine management and structural variables. Balancing the data for the target column, Performance (2024), was addressed by applying the SMOTE technique (if needed) to counteract any potential class imbalance, thereby ensuring a more reliable model evaluation.

After preparation, the dataset remained at 391 records, capturing a sufficiently diverse combination of demographic, psychological, and organizational dimensions for our experiments. For the performance classification tasks, each record was labeled according to Performance (2024) (e.g., “Fully Meets Expectations,” “Exceeds expectations,” etc.), while also retaining related labels (such as Perceived Effectiveness, Appreciation and Recognition, and Exceeding Role Expectations) to support more profound analysis. After completing these critical cleaning and feature-engineering steps, the dataset was fully primed for the subsequent modeling workflow, including the genetic algorithm, based feature selection, hyperparameter tuning, and final performance evaluation.

4.3 Configurations and Settings

All experiments have been conducted on a Windows computer with a base of a Legion 5 15ARH05H and an AMD Ryzen 7 4800H CPU at 2.90 GHz and Radeon Graphics. Code run in Python 3.9.21 with Jupyter Notebook. Key libraries and their versions include NumPy 1.26.4, pandas 2.2.3, scikit-learn 1.5.2, and XGBoost 2.1.1. Replication of experiments can be facilitated through the installation of libraries above in a Python

environment (e.g., with pip install numpy==1.26.4 pandas==2.2.3 scikit-learn==1.5.2 xgboost==2.1.1) and run of included Jupyter Notebook.

4.4 Evaluation Matrix

4.4.1 Confusion Matrix

A confusion matrix is a two-dimensional visualization format for a supervised algorithm's performance. It is most applicable in statistical classification and shows correct and incorrect model predictions concerning actual classes in a specific dataset. The two-dimensional matrix has one axis for predicted classes and one axis for actual classes, such as in Figure 4.1. Metrics in use include True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). True Positive (TP) occurs when a model accurately predicts a positive class, and True Negative (TN) occurs when a model accurately predicts a negative class. On the other hand, False Positive (FP) occurs when a model wrongly predicts a positive class, and False Negative (FN) occurs when a model wrongly predicts a negative class (Ajagbe et al., 2022; Y. Zhang et al., 2021).

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Figure 4.1: Confusion Matrix

The confusion matrix provides a detailed breakdown of model predictions, showing how often the model is correct and how it fails (mixing up positives as negatives or vice versa). This is particularly useful in contexts where the cost of a false alarm (FP) may differ from the cost of a missed detection (FN).

4.4.2 Accuracy

Accuracy measures the proportion of correctly classified instances (both positives and negatives) out of all instances:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.1}$$

Accuracy is easy to interpret and often sufficient if the dataset is balanced (i.e., roughly an equal number of positive and negative examples). However, in highly imbalanced datasets, accuracy alone can be misleading because a model might achieve high accuracy simply by predicting the majority class most of the time.

4.4.3 Precision

Precision, or Positive Predictive Value, measures the proportion of true positives among all predicted instances positives:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4.2}$$

Precision indicates how *precise* the model's positive predictions are - i.e., among all instances predicted to be positive, how many are actually positive? This is especially important in scenarios where false positives are particularly undesirable. For example, in spam detection, an email wrongly flagged as spam may cause important messages to be lost.

4.4.4 Recall

Recall (also called *Sensitivity* or *True Positive Rate*) is the ratio of true positives to the total actual positives:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4.3}$$

Recall indicates how well the model can find all positive examples. A high recall means the model correctly identifies most of the actual positives. This is especially important when missing a positive instance (false negative) is costly or dangerous, such as disease diagnosis or fraud detection.

4.4.5 F1-Score

The F1-Score is the harmonic mean of precision and recall, combining both in a single metric:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.4}$$

F1-Score balances precision and recall. It is particularly useful for imbalanced datasets where high accuracy might be misleading. By emphasizing both precision and recall, F1-Score ensures that the model identifies as many positive samples as possible and maintains accuracy in those positive predictions.

4.4.6 Receiver Operating Characteristic (ROC) Curve

A ROC Curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various decision thresholds:

- **True Positive Rate (TPR)** or *Recall*

$$TPR = \frac{TP}{TP+FN} \tag{4.5}$$

- **False Positive Rate (FPR):**

$$FPR = \frac{FP}{FP+TN} \tag{4.6}$$

The ROC curve shows the trade-off between TPR (sensitivity) and FPR (1 – specificity) across different threshold settings. The Area Under the Curve (AUC) is often used as a summary measure; it ranges from 0.5 (no discrimination) to 1.0 (perfect classification).

The ROC curve helps us visualize how well the model distinguishes between classes across different thresholds, which can be more informative than a single metric. AUC shows the likelihood that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance. This is especially valuable when we do not have a fixed decision threshold and want to evaluate model performance over a range of sensitivity–specificity trade-offs.

4.5 Implementation

This section introduces our overall prediction methodology for employee performance classification. There are four principal steps in our methodology. First, we normalize and preprocess raw survey data for uniformity and tackle class imbalances. Second, a genetic algorithm (GA) is then utilized in order to gain access to the most effective subset of features and, in the process, simplify dimensionality and maximize model efficiency. Next, several predictive models, XGBoost, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), are systematically trained and tuned with grid search for hyperparameter settings. Finally, the performance of each optimized model is evaluated over a hold-out test set.

4.5.1 Data Preprocessing

The dataset involved in this study was taken out of Survery_Final.xlsx and entails a range of demographic, performance impact and performance-related factors. Prior to model development, a series of preprocessing operations were performed:

1. Feature Encoding: Since the target dataset consisted of both numerical and categorical feature types, label encoding was performed to convert textual variables (e.g., sectors and job titles) into numerical representations compatible with most machine learning packages.
2. Removing Irrelevant Columns: Certain columns, such as past-year performance values or irrelevant feature values determined through expert analysis, were eliminated to narrow down the analysis to the most relevant feature values directly related to the employee performance output.
3. Balancing via SMOTE: SMOTE was utilized to mitigate the imbalance in the target class distribution. To counteract this, the SMOTE algorithm oversampled the minority classes and produced a balanced dataset. This was performed in an attempt to prevent models from developing a bias towards the majority classes in prediction.

Finally, an 80:20 training-testing split was adopted to train the models over a fairly significant subset of the dataset and reserve an independent portion for eventual testing.

4.5.2 Genetic Algorithm for Feature Selection

To systematically downsize the feature dimensionality of the dataset, a genetic algorithm (GA) was used, with an objective of searching for an optimal subset of features. The GA initiated with a population of 200, with

each represented in a form of a binary array specifying whether a feature is selected (1) or omitted (0). Over the course of 150 generations, a fitness function guided these individuals' evolution, where each feature subset's fitness was determined by training a model and evaluating its performance (e.g., average accuracy and F1-score) on a validation split.

Roulette wheel selection was used to select fitter individuals probabilistically and uniform crossover blended traits from the chosen parents, creating offspring that integrate features from both. A base mutation rate of 0.1 encouraged diversity by randomly flipping bits in the offspring's binary representation. Additionally, the mutation rate is adapted dynamically according to the variance in the population's fitness, balancing exploratory and exploitative behaviours in the algorithm. After 150 generations, the GA converged to a final "best chromosome," indicating which subset of features yielded the strongest predictive performance. This feature subset was then used to train and optimize the machine learning models.

Table 4.1: Genetic Algorithm Approach

Input: X, Dataset for feature selection.
Input: y, Target variable for the dataset (Employee Performance).
Input: POP_SIZE, Population size for the genetic algorithm.
Input: NUM_GENERATIONS, Number of generations for the genetic algorithm.
Input: MUTATION_RATE, Initial mutation rate for the genetic algorithm.
Output: Best Feature Set, Best combination of features for prediction.
Output: Best Score, Performance score of the best feature set.
Procedure:
Initialize Constants:
⟹SET POP_SIZE to 200, i.e., number of individuals in the population.
⟹ SET NUM_GENERATIONS to 100, i.e., number of iterations the genetic algorithm will perform.

⟹ SET MUTATION_RATE to 0.1, i.e., initial probability of mutating a gene in an individual.

Preprocess Data:

(1) Encode categorical features to convert them into numerical format suitable for machine learning algorithms.

(2) Drop unnecessary columns to simplify the dataset.

(3) Balance the dataset using SMOTE to improve performance on imbalanced datasets.

Genetic Algorithm Execution:

for generation = 1 to NUM_GENERATIONS do

(1) Create population: Generate a new set of individuals (feature sets) if it's the first generation; otherwise, evolve the population through selection, crossover, and mutation.

(2) Evaluation: Evaluate the fitness of each individual in the population by selecting features based on the individual's genes, training a model, and calculating its performance.

(3) Selection: Select individuals for the next generation using roulette wheel selection, favoring individuals with higher fitness.

(4) Crossover: Perform uniform crossover among selected individuals to create the next generation.

(5) Applying Mutation: Apply mutation to the offspring to introduce genetic diversity.

(6) Adjusting Mutation Rate: Adjust mutation rate dynamically based on the variance of fitness scores to balance exploration and exploitation.

end for

Output Best Feature Set and Score:

After all generations, return the best feature set and its corresponding performance score as the output of the genetic algorithm.

4.5.3 Classifier Training and Hyperparameter Tuning

Subsequent to feature selection, five machine learning algorithms – XGBoost, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) – were executed over the reduced feature subset that had been uncovered through Genetic Algorithms (GA). Thereafter, a grid search hyperparameter tuning exercise was conducted for each model. It entails testing a variety of sets of parameters in a systemic manner, with a view towards finding the most ideal configuration.

1. Gradient Boosting Classifier

In the case of Gradient Boosting, grid search was performed in a systemic manner, such as for a learning rate, a maximum tree depth, a boosting stage count, a subsampling proportion, and a minimum samples for a split. Following grid search, an ideal configuration was determined to have a 0.2 learning rate, a 5 maximum depth, 100 estimators, a 1.0 subsample proportion, and a 2 minimum samples split. This configuration is particularly efficient in terms of model complexity and training speed.

2. XGBoost Classifier

In the XGBoost experiments, three factors, including the max tree depth, learning rate, and number of estimators, were prioritized. In terms of grid search, an ideal combination of a 0.04 learning rate, a maximum tree depth of 7, and 90 estimators were generated. It has been confirmed that such a balanced model can help in overfitting but not at the cost of complex patterns in the data.

3. Random Forest Classifier

For Random Forest, tree number, maximum depth, feature selection approaches, and split criterion were explored. With grid search, an ideal configuration of 300 estimators, a maximum depth of 10, sqrt for max_features, and minimal leaf and split (min_samples_leaf = 1 and

min_samples_split = 2) for feature selection and split determination was determined. That configuration maximizes both individual and ensemble tree depth.

4. K-Nearest Neighbors (KNN) Classifier

The neighbor count, distance function, and weighting scheme hyperparameters were varied to find the best hyperparameters. The best performance for the model with 3 neighbours, Manhattan distance, and distance weighting was achieved. That configuration maximizes preference for neighboring points, and therefore, maximizes accuracy for determination of a neighborhood for classification.

5. Support Vector Machine (SVM) Classifier

The analysis then checked the impact of various kernels (e.g., RBF, polynomial) and tuned parameters like C (regularization strength) and gamma (kernel coefficient). The best configuration found via grid search is an RBF kernel with C = 1 and gamma = 0.1. That choice will yield a good trade-off between margin maximization and the adaptability of the model.

By applying grid search to all classifiers, an exhaustive search over hyperparameters was assured, and hyperparameters that optimized performance metrics over training data were selected. Besides, all grid search was conducted via cross-validation, and therefore, our models were safeguarded against overfitting to individual folds in training sets.

It should be noted that in selecting the five machine learning classifiers, Gradient Boosting, XGBoost, Random Forest, K-Nearest Neighbours (KNN), and Support Vector Machine (SVM), the researcher prioritised models that balance predictive performance with interpretability, particularly due to the practical requirements of Bahrain's public-sector context. While deep learning models such as neural networks offer strong

generalization on large datasets, they were not adopted in this study for several methodological and empirical reasons.

Firstly, Support Vector Machines (SVM) are well-established in handling small-to-medium-sized datasets, such as the current sample size of n = 391, with high resistance to overfitting and strong boundary discrimination, especially when combined with RBF kernels. Secondly, Random Forests were chosen for their robustness against noise, ability to model complex feature interactions, and their suitability for multi-class classification, all while maintaining explainability through SHAP values, which is critical in public sector HR analytics. These factors aligned with the need for transparent model behavior, as opposed to the "black-box" nature of most deep learning architectures.

Additionally, this selection was informed by prior empirical research conducted by the researcher entitled "Optimizing Employee Performance Prediction Using Machine Learning with Genetic Algorithm-Based Feature Selection", accepted for publication in the International Journal of Management Practice. That study used a benchmark HR dataset from Kaggle (n = 1470) to evaluate the same five classifiers after applying genetic algorithm-based feature selection. The study showed that SVM, XGBoost, and Gradient Boosting consistently outperformed deep learning approaches not only in accuracy and F1-score but also in computational efficiency and interpretability.

Finally, the findings of this thesis were benchmarked against internationally published studies to validate the relative performance of the selected models. This comparative review confirmed that the classifiers employed in this study perform on par with, or better than, similar implementations found in the literature, thereby supporting the generalizability and methodological soundness of the model selection process.

4.5.4 Features Interpretability techniques

4.5.4.1 Feature Importance

In the present experiments, a decision tree classifier was employed owing to its natural interpretability and simple method of determining the importance of features. Decision Trees automatically estimate each feature's importance based on how much it reduces impurity or error at each split, making it a natural choice for transparent, explainable modelling. In order to ascertain that a high-performing model had been identified, a range of hyperparameters – including maximum depth, minimum samples to split, and splitting criteria (e.g. Gini vs. entropy) – were tuned using a Grid Search with five-fold cross-validation. The systematic search identifies hyperparameter settings that yield optimal predictive accuracy, while cross-validation prevents overfitting by averaging over multiple data partitions.

Once the optimal Decision Tree model had been created, the feature importance values were revealed, thereby determining the extent to which each feature was responsible for constituting the model's prediction. The importance scores were then plotted in a bar plot to determine the top 10 most influential features. The process results in a brief yet unambiguous picture of what inputs most impact model results.

Concentrating on these high-impact features can help practitioners develop a more nuanced understanding of the underlying relationships in the data, potentially guiding feature engineering and data collection strategies in future studies. The entire process adheres to established conventions for assessing feature importance in tree-based models (Pudjihartono et al., 2022; Wu et al., 2023).

4.5.4.2 Decision Tree with SHAP

In the present study, the decision was made to use a Decision Tree Classifier for the following key reasons. First, Decision Trees are naturally interpretable, breaking down decision-making into a cascade of clear, hierarchical rules. Second, SHAP's TreeExplainer is optimized explicitly for tree models, enabling the swift and accurate calculation of SHAP values by leveraging the tree structure. This efficiency is particularly beneficial in the present context, as is the necessity to compute explanations over a multi-class problem with five classes. Although Support Vector Machines (SVMs) are an alternative and sometimes offer higher predictive power, their explanation would typically rely on the KernelExplainer. This model-agnostic approach is computationally heavier and less tailored to the specific properties of the model. Thus, for the present study, the Decision Tree offers the optimal trade-off between interpretability, computational efficiency, and applicability to multi-class classification, making it possible to conduct insightful analysis of feature contributions with SHAP.

4.6 Summary

This chapter presents an experimental analysis of the employee performance prediction model, reporting dataset preparation, metrics employed in evaluation, and machine learning approaches. The dataset consists of 391 records collected over 28 days, capturing demographic details, work aspects, and job performance indicators. The data was preprocessed to yield a cleansed dataset for predictive modeling, which involved cleaning, label encoding, and SMOTE-based class unbalance handling.

The experimental procedure was conducted on a machine with a Windows OS installed with an AMD Ryzen 7 processor, using Python 3.9 in conjunction with packages like NumPy, pandas, scikit-learn, and

XGBoost. The evaluation process was done using common classification metrics such as precision, recall, F1-score, accuracy, and AUC-ROC curves. The confusion matrix was used to determine the ability of the model to classify employee performance levels, providing a picture of misclassifications and improving decisional thresholds.

A genetic algorithm (GA) was utilized for feature subset selection, minimizing the dataset to the most impactful features while decreasing dimensionality. The GA was developed over 150 generations using roulette wheel selection, crossover, and adaptive mutation rates to hone in on the subset of features. The method ensured that just the most predictive and relevant attributes were included, making the model more efficient.

Five machine learning classifiers were created and tuned: Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and XGBoost. Grid search was employed to adjust hyperparameters such as learning rate, maximum depth, and number of estimators. To enhance interpretability, SHAP (SHapley Additive Explanations) values were utilized in a Decision Tree Classifier to ascertain feature importance. The method highlighted the most significant drivers of employee performance to guide decision-makers in strengthening workforce policies. The study was able to combine data-driven modeling with feature selection and interpretability tools to yield a solid, accurate, and actionable method of forecasting public-sector employee performance.

Chapter 5
Empirical Findings and Discussion

5.1 Overview

Understanding the pivotal elements influencing employee performance is paramount to optimizing workforce productivity and organizational performance. This chapter presents empirical evidence and a discussion derived from an analysis of employee performance within the government sector in Bahrain. The research method incorporates expert interview evidence, statistical analysis, and machine learning models to enhance our understanding of performance drivers. The chapter extracts, categorizes, and cross-checks primary drivers of employee performance to ensure that the findings are both theory-informed and practical.

The empirical analysis commences with a review of employee performance influences, employing expert opinion to reduce the initial set of 54 variables to more specific factors encompassing current themes of work in the contemporary workplace, such as job security, mechanisms of performance review, hybrid work arrangements, and flexible working patterns, in keeping with the dynamic nature of work in the public sector. The factors are then mapped to existing theory to enable methodological consistency and contextual utility.

The findings are validated through correlation analysis, which is used to assess organizational and behavioural variables of interest, offering insight into motivation, leadership, work-life balance, and employee engagement dynamics. The chapter also reports the results of a genetic algorithm-based feature selection, which suggests the most predictive variables of employee performance. Furthermore, different machine learning models, such as XGBoost, Random Forest, Gradient Boosting,

KNN, and SVM, are compared in this work to assess their suitability in predicting performance levels. Finally, the chapter delves into the interpretability of such models using SHAP (SHapley Additive Explanations) and decision tree analysis to provide insights regarding the most influential features that affect employee performance. The ethical implications of AI-based performance management in providing transparency, fairness, and accountability in predictive analysis are also elaborated. The findings assist in developing a data-driven and evidence-based approach towards enhancing employee performance management in the government sector.

5.2 Identification of factors influencing employee performance in the Bahraini public sector

The expert interviews yielded insightful updates on the factors influencing employee performance in Bahrain's public sector. Informed by both participant feedback and corroborating scholarly evidence, these findings were consolidated into recommended additions, modifications, and removals of the original list of 54 factors. The changes address emerging workplace challenges, such as the push for flexible or hybrid working arrangements, and refine existing constructs to better capture Bahrain's administrative realities.

A central outcome of these interviews was the introduction of new factors seen as pivotal for understanding public-sector performance in Bahrain. For instance, "Performance Appraisal Mechanisms" emerged as a critical dimension, reflecting experts' emphasis on fairness, transparency, and strategic goal-setting in employee evaluations (Chahar, 2020). Additionally, "Commute and Accessibility" was highlighted to account for the substantial influence of traffic congestion on punctuality, stress, and productivity (Wiese et al., 2024). Experts also stressed "Job Security and

Trust" (Akgunduz and Eryilmaz, 2018), explaining that clear pathways to career stability foster higher engagement and reduce turnover. "Balanced Sanction System Practices," another newly articulated factor, underscores the importance of equitable and proportionate disciplinary measures, a notion supported by Equity Theory (Adams, 1965) and corroborated by Treviño et al. (2014).

Meanwhile, the conversation around emerging trends prompted the addition of "Hybrid Work Models," reflecting evolving preferences for flexible, technology-enabled work arrangements (Wang et al., 2021), and "Flexible Working Hours," signifying the growing acceptance of more adaptable schedules for improving work-life balance (Gan et al., 2024). Lastly, experts unified the issue of turnover and retention under "Employee Retention and Turnover," citing evidence that stable, long-serving teams strengthen organizational knowledge and morale (Hom et al., 2017).

At the same time, multiple factors were integrated and adjusted to eliminate redundancies and improve conceptual clarity. Components like "Training and Development Opportunities," "Personal Development Opportunities," and "Crisis Management Training" were consolidated under the term "Employee Development," reflecting the comprehensive approach that experts recommend for upskilling and lifelong learning. Technologically focused factors, including "Technological Advancement" and "Technological Competence and Support", were similarly regrouped under "Technological Advancement" to streamline overlapping areas. Additionally, themes centering on employee well-being, mental health, and wellness programs were consolidated into "Well-being and Mental Health" to present an integrated perspective on psychosocial support in the workplace.

Several factors were removed or deemed less relevant, often because they overlapped with more potent constructs or did not immediately influence employee performance. For instance, “Compensation and Remuneration” were excluded in favour of more nuanced reward and recognition systems, acknowledging the budgetary limitations of Bahrain’s public sector. “Environmental Sustainability Initiatives” was also deprioritized due to experts’ views on more pressing operational and service-delivery imperatives. Furthermore, context-specific considerations, such as the highly structured hierarchical frameworks in the Bahraini public sector, led to the removal or reframing of factors like “Work Autonomy and Flexibility” and “Remote Work Capability,” both of which were partially absorbed under “Hybrid Work Models.” These decisions reflect the ongoing effort to contextualize general organizational constructs to Bahrain’s unique administrative environment.

The newly introduced factors were detailed within established theoretical frameworks to maintain methodological consistency. For instance, "Performance Appraisal Mechanisms" corresponds with Goal-Setting Theory (Locke and Latham, 1990), whereas “Commute and Accessibility” is based on the Effort-Recovery Model (Meijman and Mulder, 1998). Similarly, “Job Security and Trust” is closely tied to Maslow’s Hierarchy of Needs, and “Balanced Sanction System Practices" embody key principles of Equity Theory (Adams, 1965). By anchoring these factors in recognized theories and empirical evidence, the study guarantees that the updated list of performance drivers is built on a strong conceptual basis and is ready for future empirical investigation.

The researcher serves the expert interviews to augment the initial list of factors with a valuable additional layer of depth. This collaborative process enhanced the study's analytical framework, ensuring its

comprehensive coverage of both theoretical and practical dimensions, thereby facilitating the generation of actionable insights for improving public sector performance, incorporating real-world insights that underscored the significance of Bahrain's distinctive cultural and administrative context.

As shown in Table 5.1, 46 optimal factors were identified as being the most suitable for measuring their impact on the performance of public servants in the Bahraini context, according to the experts involved. It should be noted that the literature review was referenced at this juncture when introducing new factors that were not among those extracted from the literature review in the initial phase. These new factors are indicated in Table 5.1, with the source from which they were identified as influencing employee performance.

Table 5.1: Factors Affecting Bahraini Public Sector Employee Performance

No.	Factor	Nature of Factor
1	Public Service Motivation (PSM)	
2	Job Satisfaction	
3	Work-Life Balance	
4	Employee Recognition and Reward Systems	
5	Flexible Working Hours	New Factor
6	Communication Skills	
7	Organizational Citizenship Behaviours (OCBs)	
8	Proactive Behaviour	
9	Employee Voice and Participation	
10	Feedback Culture	
11	Knowledge-Sharing Ability	
12	Competence	
13	Employee Development	
14	Digital Literacy and Skills	
15	Mentoring and Coaching	

No.	Factor	Nature of Factor
16	Personal Development Opportunities	
17	Leadership Style	
18	Supervisory Assistance	
19	Change Management	
20	Performance Appraisal Mechanisms	New Factor
21	Balanced Sanction System Practices	New Factor
22	Organizational Culture	
23	Work Climate	
24	Agility and Innovation Culture	
25	Employee Engagement	
26	Organizational Commitment	
27	Team Dynamics and Peer Relationships	
28	Organizational Structure and Clarity	
29	High-Performance Work Systems (HPWS)	
30	Technological Integration and Competence	
31	Hybrid Work Models	New Factor
32	Innovation and Creativity	
33	Job Design and Workload	
34	Emotional Intelligence (EI)	
35	Psychological Safety	
36	Employee Well-being and Mental Health	
37	Employee Autonomy	
38	Cognitive Abilities	
39	Adaptability	
40	Job Security and Trust	New Factor
41	Diversity and Inclusion	
42	Organizational Transparency	
43	Physical Work Environment	
44	Commute and Accessibility	New Factor
45	Sustainability and Ethical Practices	
46	Employee Retention and Turnover	New Factor

For an expanded and detailed presentation of qualitative findings, including comprehensive thematic analyses, insights, and recommendations derived from the expert interviews and focus group discussions conducted in this thesis, readers are encouraged to consult the researcher's published work (Alsobaey and Alkhateeb, 2025). This article provides an in-depth, standalone analysis of the qualitative phase, elaborating extensively on the factors influencing employee performance in Bahrain's public sector, thereby serving as a complementary, yet substantial, research contribution to this thesis.

5.3 Correlation Matrix

The correlation matrix offers valuable insights into the intricate relationship between organizational practices and individual competencies that drive employee performance. For instance, Public Service Motivation (PSM) is positively correlated with moderate values for Knowledge-Sharing Ability ($r = 0.5$) and Communication Skills ($r = 0.5$), indicating that intrinsically motivated staff share information effectively and communicate purposefully. Emotional Intelligence (EI) has a strong correlation with Knowledge-Sharing Ability ($r = 0.4$) and Cognitive Abilities ($r = 0.4$), suggesting that emotional sensitivity and mental acuity work together to facilitate collective problem-solving. Furthermore, Organizational Citizenship Behaviours and Proactive Behaviour are highly correlated ($r = 0.5$), meaning that when staff voluntarily exceed official role expectations, they tend to initiate transformations in work settings.

Among the most striking findings of the correlation analysis is the high correlation of High-Performance Work Systems with Agility and Innovation Culture ($r = 0.7$), underscoring the strong role of structured, supportive systems in fostering flexibility and innovative problem-solving. Supervisory Assistance also plays a prominent role, showing a

high correlation with Team Dynamics and Peer Influence (r = 0.6) and a moderate correlation with Change Management (r = 0.4), indicating the importance of leadership support during periods of change. Employee Engagement is positively correlated with Job Security and Trust (r = 0.5) and Job Satisfaction (r = 0.4), revealing the necessity of a secure and trustworthy climate for sustained performance. In the personal development context, Employee Development is strongly correlated with Personal Development Opportunities (r = 0.5), and Balanced Sanction System Practices are moderately correlated with Leadership Style (r = 0.6), illustrating the alignment of consistent managerial practices with employee development programs.

Notably, Employee Autonomy is very weakly correlated with PSM (r = 0.0), yet its moderate correlation with Job Security and Trust (r = 0.4) suggests that the advantages of autonomy may be more evident when employees feel secure and trusted. Other variables also reveal additional nuances—for instance, Digital Literacy and Skills correlate with Work-Life Balance at a high r = 0.5, while the Organizational Structure and Clarity show a modest correlation with Commute and Accessibility (r = 0.3), contributing to the overall framework that impacts performance.

These findings validate the necessity of an integrated strategy that concurrently develops individual competencies and complementary organizational practices to optimize employee performance.

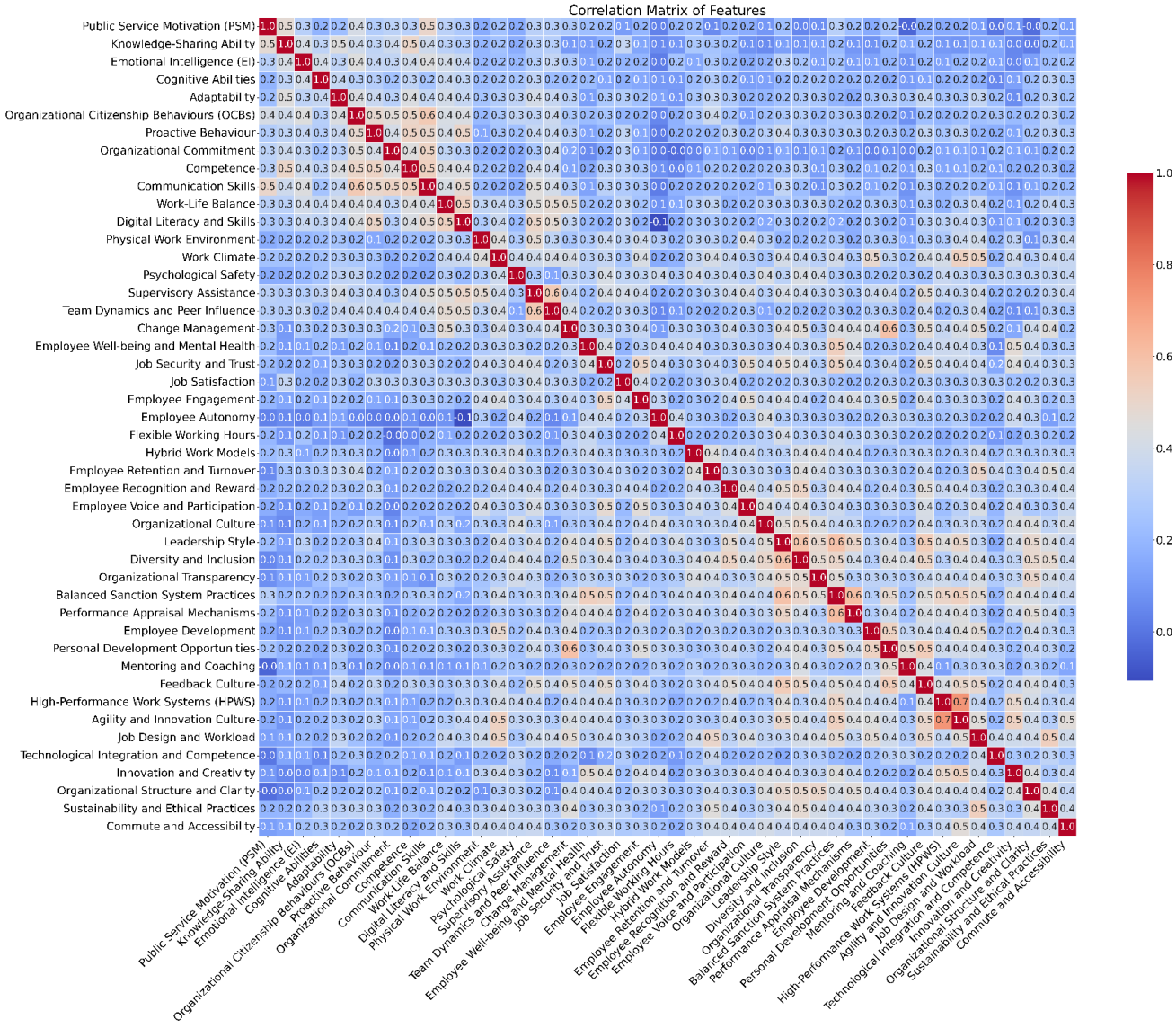


Figure 5.1: The correlation matrix of Features

5.4 Feature Selection Results (Genetic Algorithm)

5.4.1 Best Chromosome and Fitness

The Genetic Algorithm was applied to each of the five models, Gradient Boosting, XGBoost, Random Forest, KNN, and SVM, to identify optimal subsets of features from the preprocessed dataset. Each chromosome was evaluated by training the respective model on the selected features and measuring performance (e.g., accuracy, F1-score). The reported "fitness" score typically reflects an average or weighted metric (e.g., averaging accuracy and F1), indicating the quality of that chromosome's feature

subset. The following provides a summary of the chromosome with the highest score (best feature subset) found for each model, along with the final fitness score and model-specific hyperparameters. Notably, throughout all models, both organizational and psychological dimensions of employee performance recur in the chosen subsets, illustrating the multidimensional nature of effective classification in this context.

1. **Gradient Boosting:** The GA achieved a final fitness score of 0.9358, selecting 21 features from the total feature set. The resulting subset includes variables such as Public Service Motivation (PSM), Knowledge Sharing Ability, Cognitive Abilities, Work-Life Balance, Digital Literacy and Skills, Team Dynamics and Peer Influence, and High-Performance Work Systems (HPWS). Notably, including social factors (e.g., Team Dynamics) and individual factors (e.g., Cognitive Abilities) emphasizes Gradient Boosting's sensitivity to nuanced, multifaceted performance drivers.
2. **XGBoost:** The XGBoost-based GA run selected 27 features, achieving a fitness score of 0.9024. Notable features include Cognitive Abilities, Adaptability, Proactive Behaviour, Organizational Commitment, Communication Skills, Job Security and Trust, Flexible Working Hours, and Hybrid Work Models. These features suggest that XGBoost enormously benefits from capturing both individual initiative and organizational structures, reflecting the model's sensitivity to employees' capacity to adapt to changing work environments.
3. **Random Forest:** The GA converged on a fitness score of 0.9326 for the Random Forest classifier, selecting 23 features. These features include Public Service Motivation (PSM), Organizational Citizenship Behaviours (OCBs), Proactive Behaviour, Competence, Psychological Safety, Employee Well-being and Mental Health, and Employee Voice and Participation. Interpersonal and cultural dimensions (e.g., OCBs,

Psychological Safety) alongside individual competencies illustrate how Random Forest leverages a broad tapestry of workplace attributes to achieve robust predictive performance.

4. **K-Nearest Neighbors (KNN):** KNN's GA-based solution recorded a fitness score of 0.9659, the highest among the five models. The 28 selected features span both organizational and psychological domains, including Public Service Motivation (PSM), Knowledge-Sharing Ability, Organizational Citizenship Behaviours (OCBs), Proactive Behaviour, Employee Well-being and Mental Health, and High-Performance Work Systems (HPWS). The model's instance-based nature appears to benefit from a richer representation of diverse features, allowing KNN to more finely discriminate among observations by leveraging detailed individual and structural factors.
5. **Support Vector Machine (SVM):** The GA run for SVM selected 25 features overall, yielding a fitness score of 0.9464. Noteworthy features in this subset are Knowledge-Sharing Ability, Cognitive Abilities, Organizational Citizenship Behaviours (OCBs), Organizational Commitment, Communication Skills, Digital Literacy and Skills, and Personal Development Opportunities. SVM's sensitivity to distinct boundaries between classes is reflected in the emphasis on learning-related and collaborative attributes, suggesting that nuanced skill-based features strongly influence the decision boundary.

Table 5.2 lists all unique features that appeared in at least one model's best chromosome (i.e., the GA-selected subset) and indicates which models ultimately selected each feature. Several features—such as Feedback Culture, Exceeding Role Expectations, Perceived Effectiveness, and Work-Life Balance—appear frequently across multiple models, suggesting their consistent importance for predicting employee performance. Other features show more model-specific patterns, reflecting differences in how

each classifier (coupled with the GA) searches the feature space for optimal predictive subsets.

Table 5.2: Feature Selected by Machine Learning Models with Genetic Algorithm

#	Feature	Gradient Boosting	SVM	XGBoost	KNN	Random Forest
1	Public Service Motivation (PSM)	✓			✓	✓
2	Knowledge-Sharing Ability	✓	✓		✓	
3	Emotional Intelligence (EI)					
4	Cognitive Abilities	✓	✓	✓		
5	Adaptability			✓		
6	Organizational Citizenship Behaviors (OCBs)		✓		✓	✓
7	Proactive Behavior			✓	✓	✓
8	Organizational Commitment		✓	✓	✓	
9	Competence		✓	✓	✓	✓
10	Communication Skills		✓	✓	✓	
11	Work-Life Balance	✓				
12	Digital Literacy and Skills	✓	✓	✓	✓	
13	Physical Work Environment			✓		
14	Work Climate			✓		
15	Psychological Safety			✓		✓
16	Supervisory Assistance				✓	✓
17	Team Dynamics and Peer Influence	✓		✓		
18	Change Management	✓	✓	✓		
19	Employee Well-being and Mental Health	✓	✓	✓	✓	✓
20	Job Security and Trust			✓		
21	Job Satisfaction	✓				✓
22	Employee Engagement		✓	✓		✓
23	Employee Autonomy	✓		✓		✓
24	Flexible Working Hours		✓	✓		
25	Hybrid Work Models			✓	✓	✓
26	Employee Retention and Turnover		✓	✓	✓	
27	Employee Recognition and Reward	✓	✓	✓	✓	✓
28	Employee Voice and Participation	✓	✓	✓	✓	✓
29	Organizational Culture		✓	✓	✓	
30	Leadership Style	✓			✓	✓
31	Diversity and Inclusion				✓	
32	Organizational Transparency		✓		✓	✓
33	Balanced Sanction System Practices		✓			✓
34	Performance Appraisal Mechanisms	✓		✓	✓	✓
35	Employee Development				✓	
36	Personal Development Opportunities	✓	✓	✓	✓	✓
37	Mentoring and Coaching	✓	✓	✓	✓	
38	Feedback Culture		✓		✓	✓

#	Feature	Gradient Boosting	SVM	XGBoost	KNN	Random Forest
39	High-Performance Work Systems (HPWS)	✓	✓		✓	✓
40	Agility and Innovation Culture	✓	✓			
41	Job Design and Workload	✓		✓		✓
42	Technological Integration and Competence		✓			✓
43	Innovation and Creativity	✓			✓	
44	Organizational Structure and Clarity	✓	✓	✓	✓	
45	Sustainability and Ethical Practices				✓	
46	Commute and Accessibility		✓		✓	✓

5.4.2 Interpretation of the Selected Features

Whilst each model identified a unique set of features, there was significant overlap within specific categories, thereby emphasizing their relevance in predicting employee performance. Features frequently selected, such as Public Service Motivation (PSM), Knowledge-Sharing Ability, High-Performance Work Systems (HPWS), Feedback Culture, and Proactive Behaviour, underscore the significance of individual initiative, supportive environments, and open communication channels. These commonalities are consistent with the broader literature on organizational behaviour, such as Zhang (2023), Kim et al. (2024), Jatoi et al. (2024), Evans and Dobrosielska (2021) and Wang et al. (2024), which posits that employees demonstrate optimal performance when motivated, able to share knowledge, operate within effective systems, and receive constructive feedback.

Attributes related to organizational commitment, psychological safety, and personal development opportunities similarly recur across multiple subsets, indicating that secure and growth-oriented environments enable individuals to thrive, and this is consistent with the findings of S. J. Han et al. (2019). Many models also emphasize structural and cultural factors—such as organizational culture, organizational transparency, and hybrid work models—further illustrating that overarching policies, clarity in operations, and flexible work arrangements can significantly drive or

inhibit individual success, as emphasized by Blom et al. (2020), Flynn et al. (2024) and Wang et al. (2021).

Finally, certain behavioral and cognitive factors (e.g., Cognitive Abilities, Organizational Citizenship Behaviors (OCBs), and Communication Skills) appear frequently, highlighting the importance of interpersonal aptitude and willingness to go beyond basic role requirements, as stated in studies such as Nye et al. (2022), Widayati et al. (2020), and Gbarale and Lebura (2020b). The repeated inclusion of these personal and social dimensions across different algorithms suggests their robust predictive power in diverse classification paradigms. When considered as a whole, the features selected by the genetic algorithm (GA) imply a multidimensional conceptualization of employee performance. This is characterized by an integration of personal traits, workplace relationships, organizational practices, and cultural foundations. The overlap of individual features across models is indicative of their salience, whereas the differences reflect each classifier's specific position on which factors are most significant. These findings emphasize that employee success is driven by a synergy of individual attributes, supportive work environments, and formally instituted organizational systems.

5.5 Overall Model Performance

5.5.1 Performance Metrics

The classification models were evaluated on a held-out test set (20% of the dataset) using several metrics, including overall accuracy and macro-average F1-score. In addition to these summary statistics, an examination was undertaken of each model's capacity to differentiate between five distinct performance levels, ranging from exceeding expectations to requiring further development. This more nuanced analysis demonstrated that the algorithms varied in accuracy, with some models more effectively identifying participants at the high and low levels of the performance spectrum. Regarding accuracy, as shown in Figure 5.2, the SVM model achieved the highest score, 92.51%. Random Forest followed it at 91.63%, KNN at 91.18%, Gradient Boosting at 90.75%, and XGBoost at 89.43%. For all the models, specific nuances of the performance categories presented more significant difficulties in classifying than others, reflecting variations in real-world employee performance. Overall, these results indicate that both the choice of algorithm and hyperparameter tuning significantly impact the success of predictions and interpretations of employee performance.

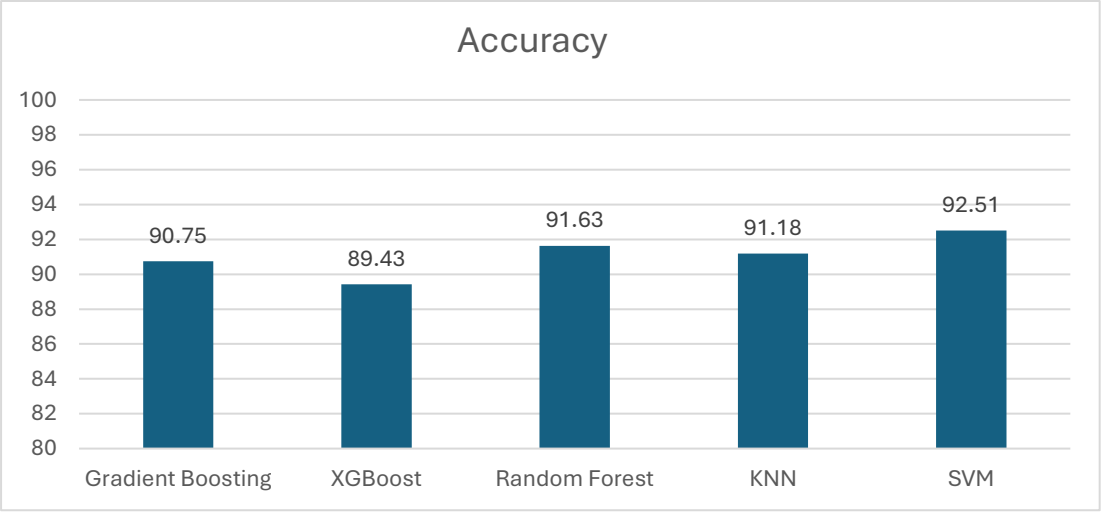


Figure 5.2: The Accuracy of Classification Models

1. **Gradient Boosting:**

Gradient Boosting achieved overall accuracy of approximately 0.91, indicating good predictive ability for all levels of performance. Notably, it predicted employees at the lower levels of performance (Needs Improvement and Partially Meets Expectations) with perfect precision and recall (both 1.00), indicating its reliability in targeting those who need development. For higher-tier categories (Far Exceeds, Exceeds, and Fully Meets Expectations), recall ranged from 0.81 to 0.93, indicating the model's ability to distinguish between high performers. The careful tuning of learning rate, subsampling, and number of estimators was likely accountable for these well-balanced findings.

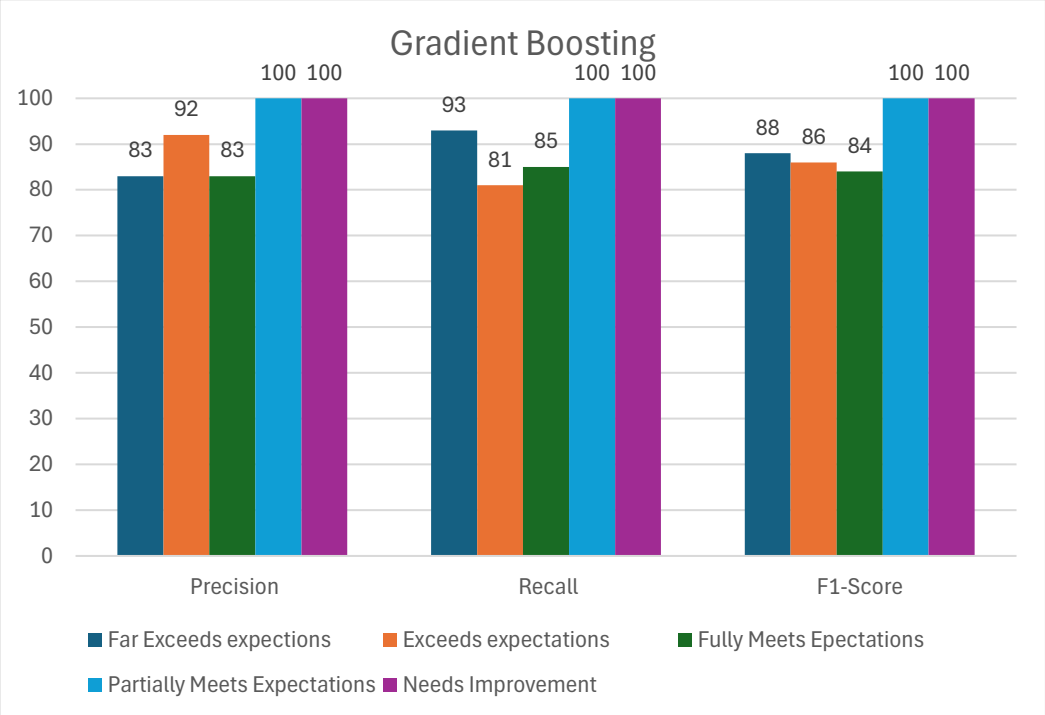


Figure 5.3: Performance Metrics of Gradient Boosting

2. **XGBoost:**

XGBoost recorded accuracy of approximately 0.89. Similar to Gradient Boosting, it had near-perfect detection for employees

requiring improvement or partially meeting expectations. The model had somewhat lower recall (0.79–0.90) for top performers, meaning that it sometimes misclassified a few individuals in that category. Nevertheless, precision was still high for those upper performance categories, meaning that the times XGBoost classified someone as a top performer, it was generally right.

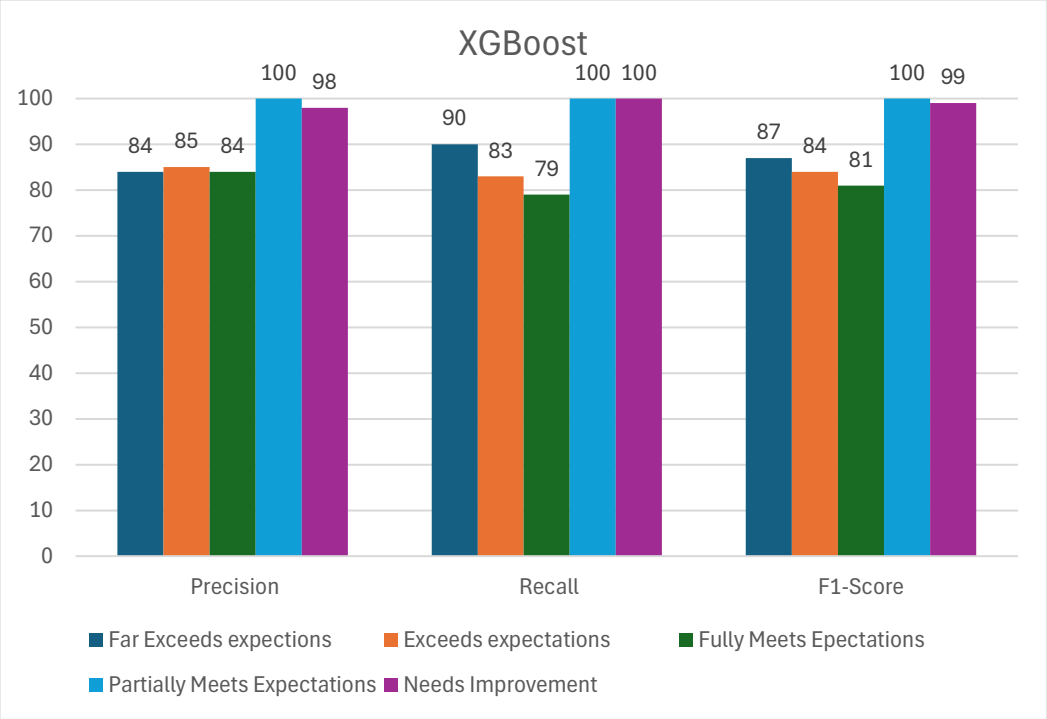


Figure 5.4: Performance Metrics of XGBoost

3. **Random Forest**

Random Forest achieved an accuracy of around 0.92. It also identified underperformers with precision and recall ranging from 0.97 to 1.00 for the lower performance levels. Precision ranged from 0.83 to 0.95, and recall ranged from 0.83 to 0.90 for the higher performance levels. These rates show that while confusion between higher performance levels was present, Random Forest still maintained a good ability to distinguish between those levels, thanks to its ensemble of diverse decision trees.

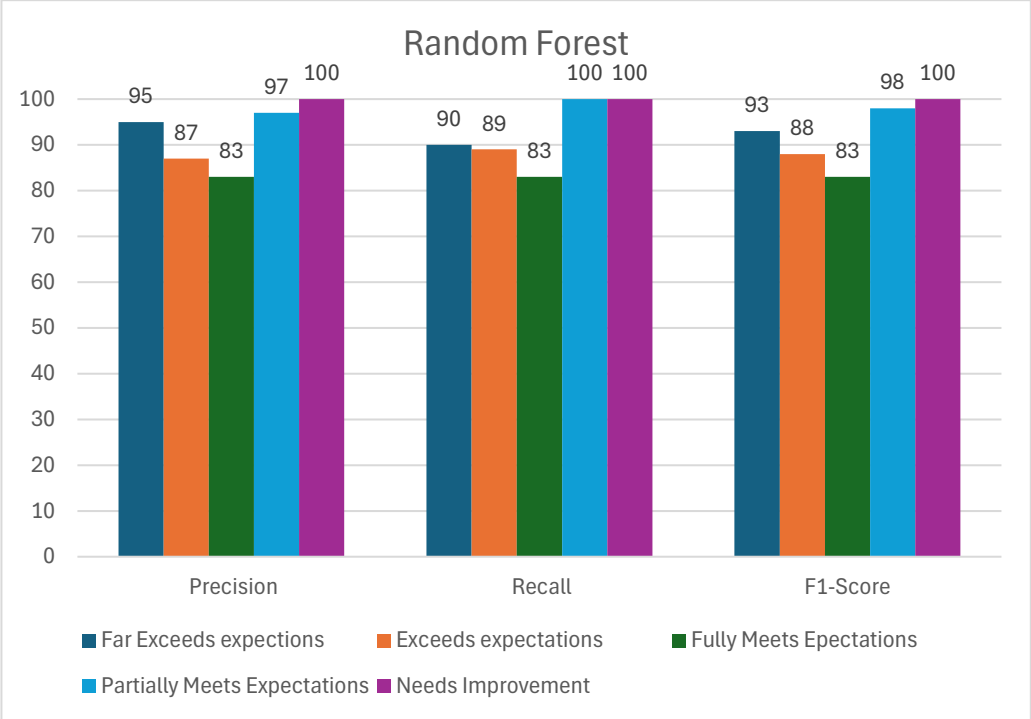


Figure 5.5: Performance Metrics of Random Forest

4. **K-Nearest Neighbors (KNN):**

KNN reached accuracy of about 0.91, comparable to the ensemble models. Its detection of underperformers remained robust, with precision and recall at or near 0.89 for workers partially meeting expectations and 1.00 for those needing improvement. For high performers, precision and recall were 0.79–0.93, showing the model's ability to differentiate between higher levels of performance. The careful choice of three neighbors, Manhattan distance, and distance weighting assisted KNN in performing well with intricate feature patterns in the data.

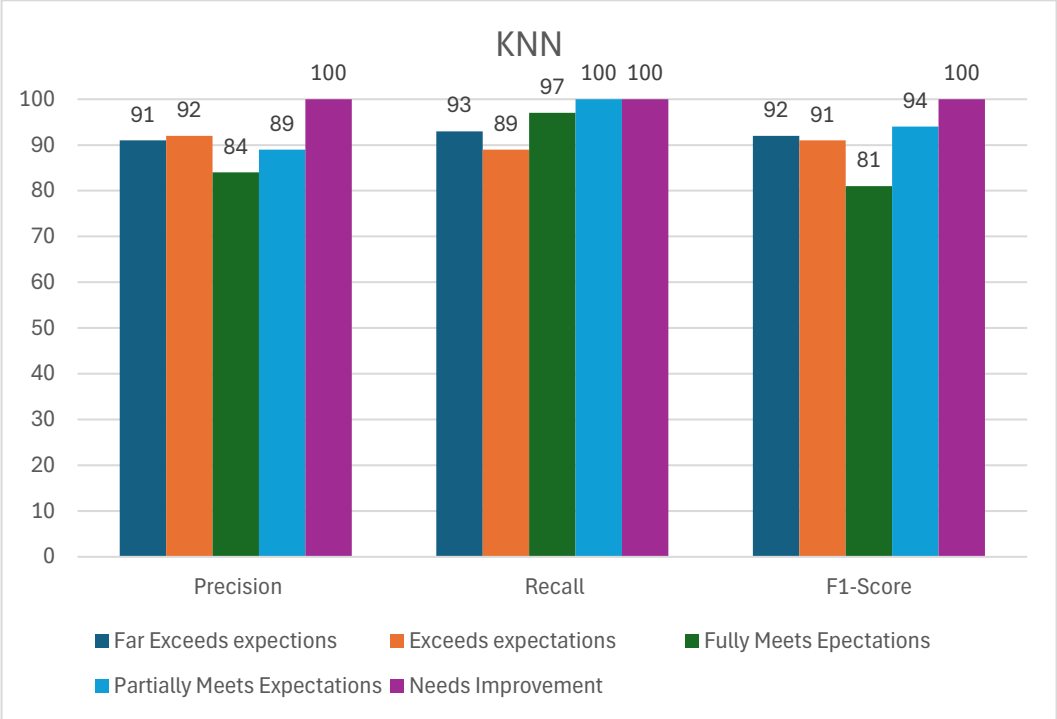


Figure 5.6: Performance Metrics of KNN

5. Support Vector Machine (SVM)

   SVM emerged as the best-performing classifier with an accuracy near 0.93. The model exhibited near-perfect recall for those far exceeding expectations (0.98) and those needing improvement (1.00), while also achieving high precision and recall (0.82–1.00) for employees fully or partially meeting expectations. Its superior discrimination capability appears linked to the RBF kernel combined with $C = 100$ and $\gamma = 0.1$, which helped capture complex relationships without significant overfitting. SVM's consistently high scores across all performance levels highlight its strength in separating employees with subtle performance differences.

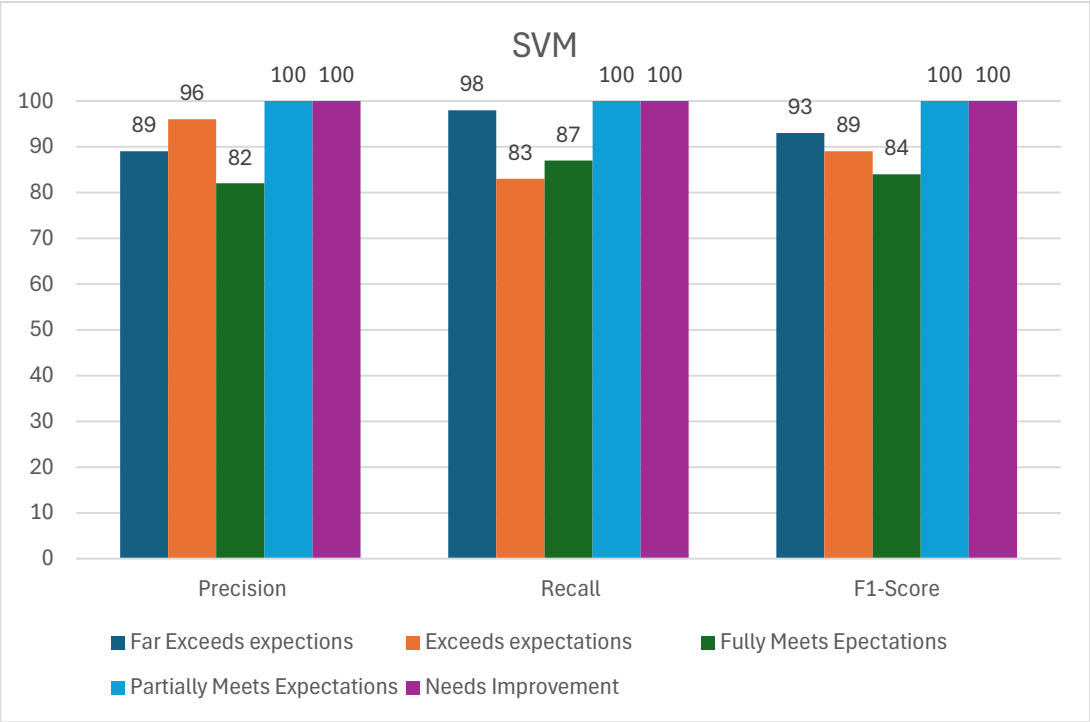


Figure 5.7: Performance Metrics of SVM

The five models, Gradient Boosting, XGBoost, Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), demonstrated strong performance in classifying employees across multiple performance tiers. The ensemble methods (Gradient Boosting, XGBoost, and Random Forest) and KNN consistently achieved high accuracy (ranging from about 0.89 to 0.92), excelling particularly at identifying underperformers (needs improvement or partially meets expectations) with near-perfect precision and recall.

Meanwhile, SVM emerged as the best-performing model, reaching an accuracy of approximately 0.93. It showed consistently high precision and recall across both lower- and higher-performance categories, suggesting that its carefully tuned hyperparameters $C = 100\ and\ \gamma = 0.1$ with an RBF kernel) captured complex patterns in the data. These findings highlight the importance of robust feature selection and hyperparameter optimization in achieving high accuracy for multi-tier performance classification.

5.5.2 Comparison of Machine Learning Model Accuracy with and Without Genetic Algorithm

The Genetic Algorithm (GA) has proven to be a powerful optimization technique for enhancing machine learning model performance. Without GA, the models achieved the following accuracy levels: Gradient Boosting (89.87%), XGBoost (85.93%), Random Forest (90.75%), KNN (88.99%), and SVM (92.07%). However, after applying GA for hyperparameter tuning, all models exhibited notable improvements: Gradient Boosting increased to 90.75%, XGBoost saw a significant boost to 89.43%, Random Forest improved to 91.63%, KNN rose to 91.18%, and SVM reached 92.51%. These improvements highlight GA's ability to efficiently explore the hyperparameter space, avoiding local optima and achieving better model generalization. The consistent accuracy gains demonstrate that GA is a valuable tool for optimizing machine learning models, leading to enhanced predictive performance and robustness.

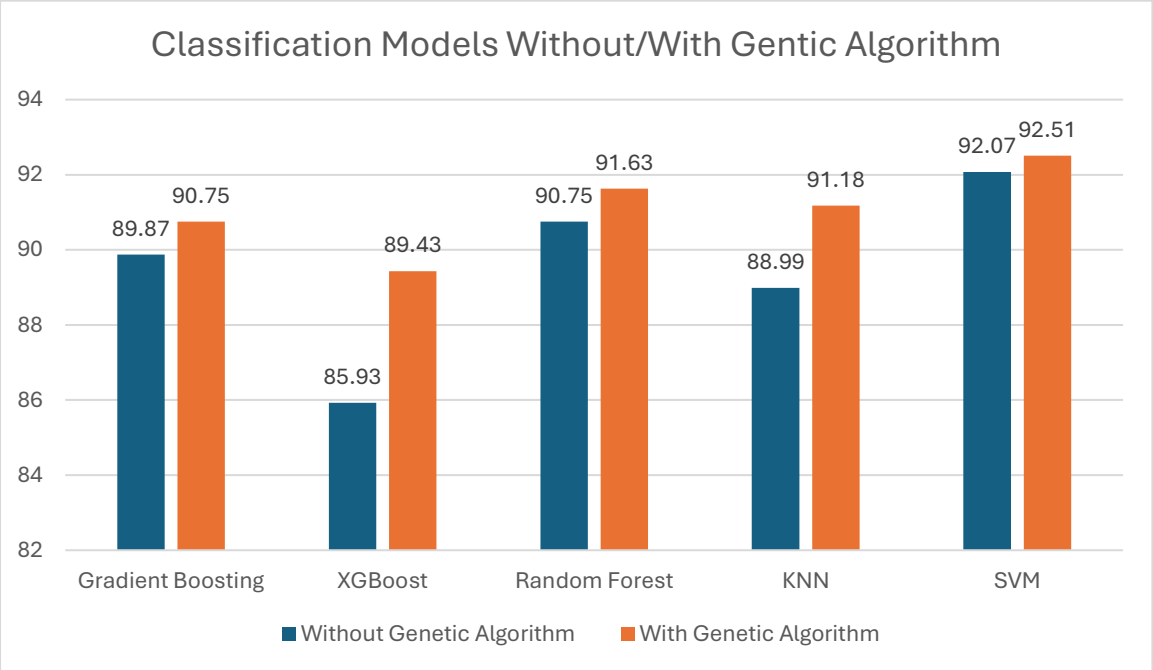


Figure 5.8: Comparison of Models Accuracy with/without Genetic Algorithm

5.5.3 ROC Analysis

In addition to the standard performance metrics of accuracy and F1-score, we examined the Receiver Operating Characteristic (ROC) curves for each of the five models (Random Forest, Gradient Boosting, KNN, XGBoost, and SVM) under a multi-class setting. For each class label, Exceeds

Expectations, Far Exceeds Expectations, Fully Meets Expectations, Needs Improvement, and Partially Meets Expectations, we adopted a one-vs.-rest binarization approach to compute the True Positive Rate (TPR) and False Positive Rate (FPR) across a spectrum of decision thresholds. The resulting area under each ROC curve (AUC) encapsulates each model's ability to discriminate between the target class and all other classes.

1. Gradient Boosting:

The Gradient Boosting model displays high AUCs across all five categories. In particular, Needs Improvement and Partially Meets Expectations attain a perfect AUC of 1.00, indicating flawless separation for lower-performing employees. Far Exceeds Expectations follows closely at 0.99, while Exceeds Expectations and Fully Meets Expectations record 0.98 and 0.97, respectively. These results underscore Gradient Boosting's strong balance between sensitivity and specificity, even for subtler distinctions among high performers.

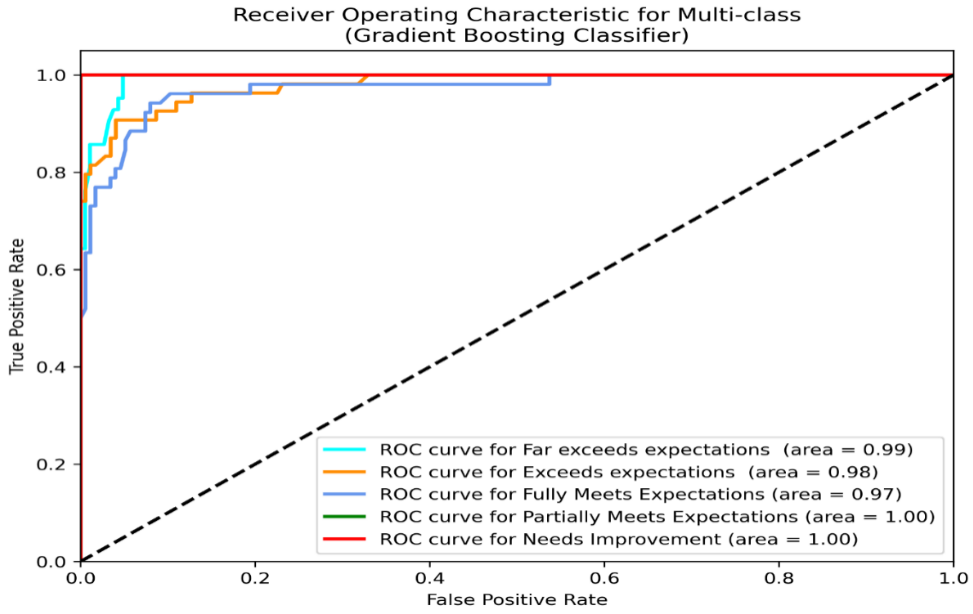


Figure 5.9: ROC Analysis - Gradient Boosting

2. XGBoost

XGBoost exhibits similarly high discriminatory power. As with Gradient Boosting, Needs Improvement and Partially Meets Expectations both reach an AUC of 1.00. Far Exceeds Expectations is close behind at 0.99, and both Exceeds Expectations and Fully Meets Expectations come in at 0.97. While minor fluctuations may arise relative to Gradient Boosting, these high AUCs confirm XGBoost's robust capacity to handle complex decision boundaries across diverse employee performance categories.

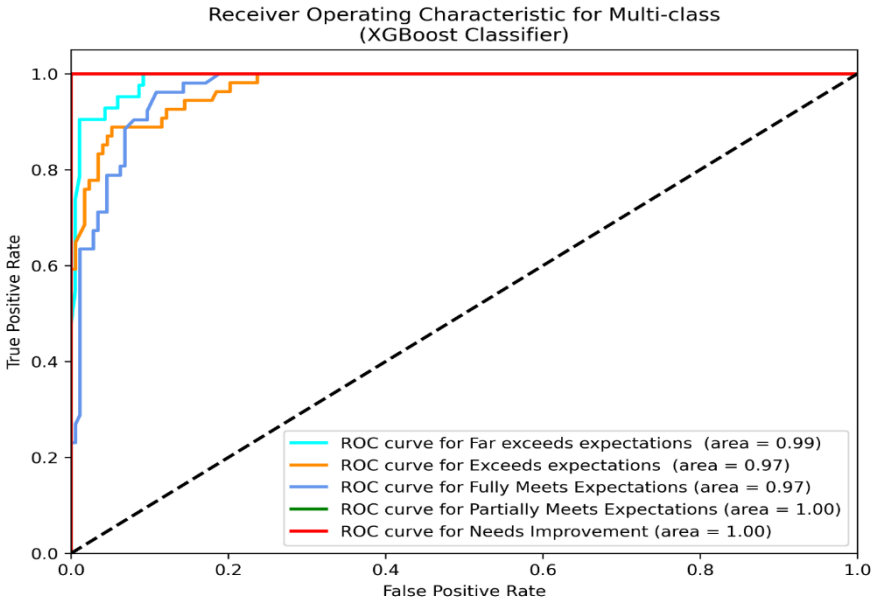


Figure 5.10: ROC Analysis - XGBoost

3. Random Forest

Random Forest's ROC curves also reflect strong separability. Far Exceeds Expectations, Needs Improvement, and Partially Meets Expectations each reach 1.00 AUC—indicating near-flawless identification of employees in these categories. Exceeds Expectations and Fully Meets Expectations each post 0.98, aligning with the high precision and recall observed in the confusion matrix. This performance highlights Random Forest's resilience and consistency, especially for clearly defined performance tiers.

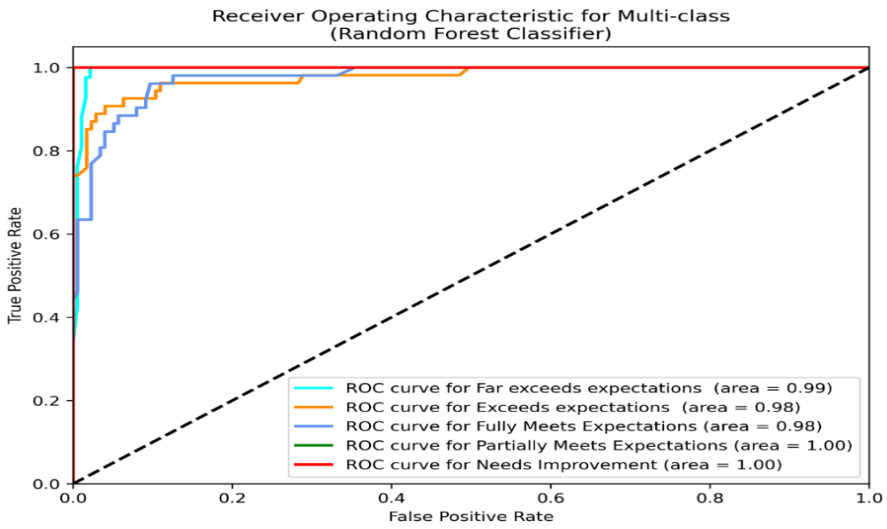


Figure 5.11: ROC Analysis - Random Forest

4. K-Nearest Neighbors (KNN)

KNN provides robust performance in the ROC analysis, led by a perfect AUC of 1.00 for Needs Improvement. Far Exceeds Expectations and Partially Meets Expectations follow at 0.99, while Exceeds Expectations and Fully Meets Expectations show 0.95 and 0.93, respectively. The slight dip in fully meeting expectations suggests some overlap among mid- to high-level performers, yet the near-perfect separation for the other categories demonstrates KNN's strength when using Manhattan distance and distance-weighted voting for distinctly clustered groups.

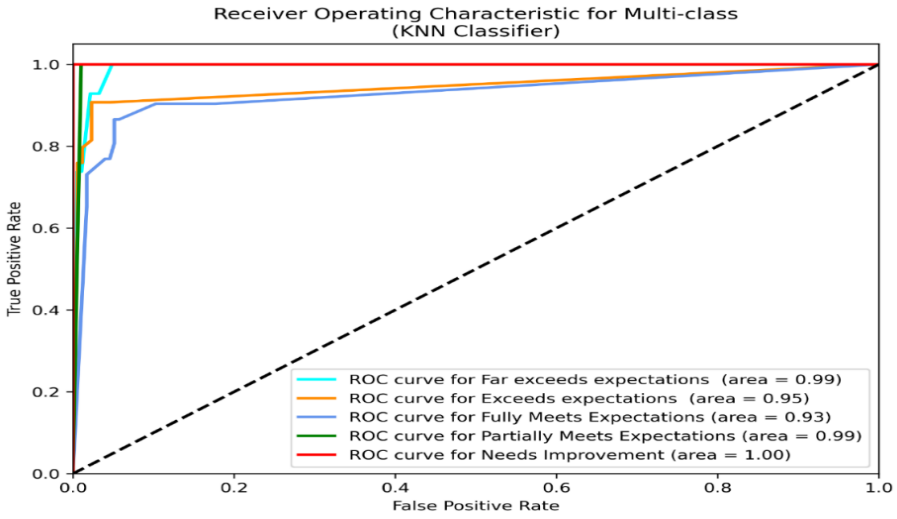


Figure 5.12: ROC Analysis - KNN

5. Support Vector Machine (SVM)

SVM nearly perfects its multi-class separation for both lower- and higher-tier categories. Needs Improvement and Partially Meets Expectations each achieve 1.00 AUC, while Far Exceeds Expectations follow at 0.99. Exceeds Expectations and Fully Meets Expectations are separated with AUC values of 0.98 and 0.97, respectively. These findings mirror the earlier precision and recall metrics, indicating that the RBF kernel—optimized with a high C value and moderate γ—effectively captures non-linear boundaries without substantial misclassification in more challenging performance splits.

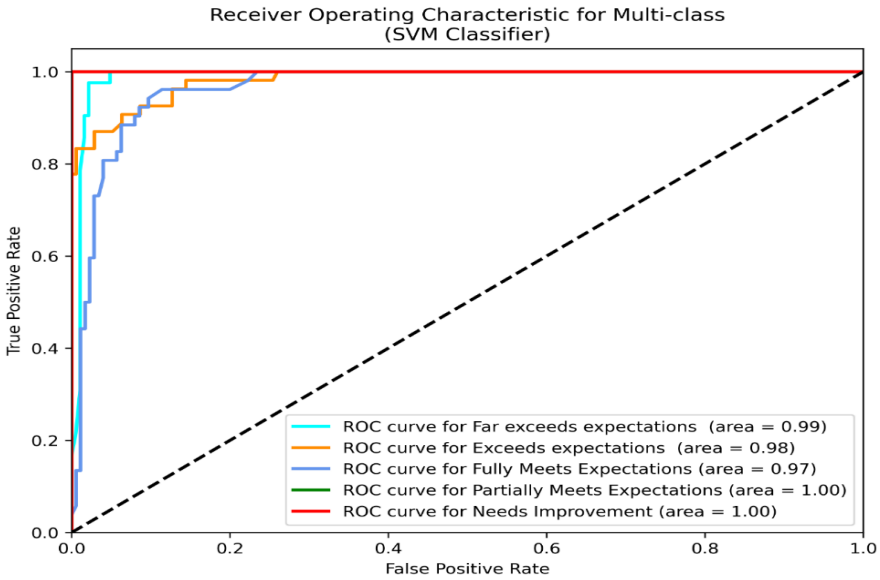


Figure 5.13: ROC Analysis - SVM

Taken together, the multi-class ROC curves and AUC scores reinforce the accuracy and F1 results previously observed. All five models excel at identifying Needs Improvement and Partially Meets Expectations (regularly scoring 1.00 AUC), suggesting that the chosen features cleanly distinguish lower-performing employees. The higher-performance categories (Exceeds, Far Exceeds, Fully Meets) also achieve commendable AUC values (ranging roughly from 0.93 to 0.99), although minor dips reflect the natural challenge of separating closely related performance tiers.

Overall, these ROC analyses confirm that, when paired with the genetic algorithm–selected features, each classifier is highly adept at discriminating among multiple performance levels.

5.5.4 Confusion Matrix

In addition to overall accuracy and F1-scores, confusion matrices offer a more granular view of each model's ability to correctly (and incorrectly) classify employees into the five performance categories:

- Far Exceeds Expectations
- Exceeds Expectations
- Fully Meets Expectations
- Needs Improvement
- Partially Meets Expectations

By examining true positives, false positives, and false negatives at the class level, we can better understand how each model handles the unique challenges posed by multi-class performance prediction.

1. Gradient Boosting

   From the Gradient Boosting confusion matrix, Needs Improvement and Partially Meets Expectations show perfect classification—no employee in either of these lower performance tiers is misclassified. Meanwhile, most errors occur among the higher performance groups, particularly between Exceeds Expectations and Fully Meets Expectations, indicating that individuals who just meet expectations and those who exceed them share overlapping features. Still, the near-accurate separation of all other categories underscores Gradient Boosting's reliable handling of both strong and underperforming employees.

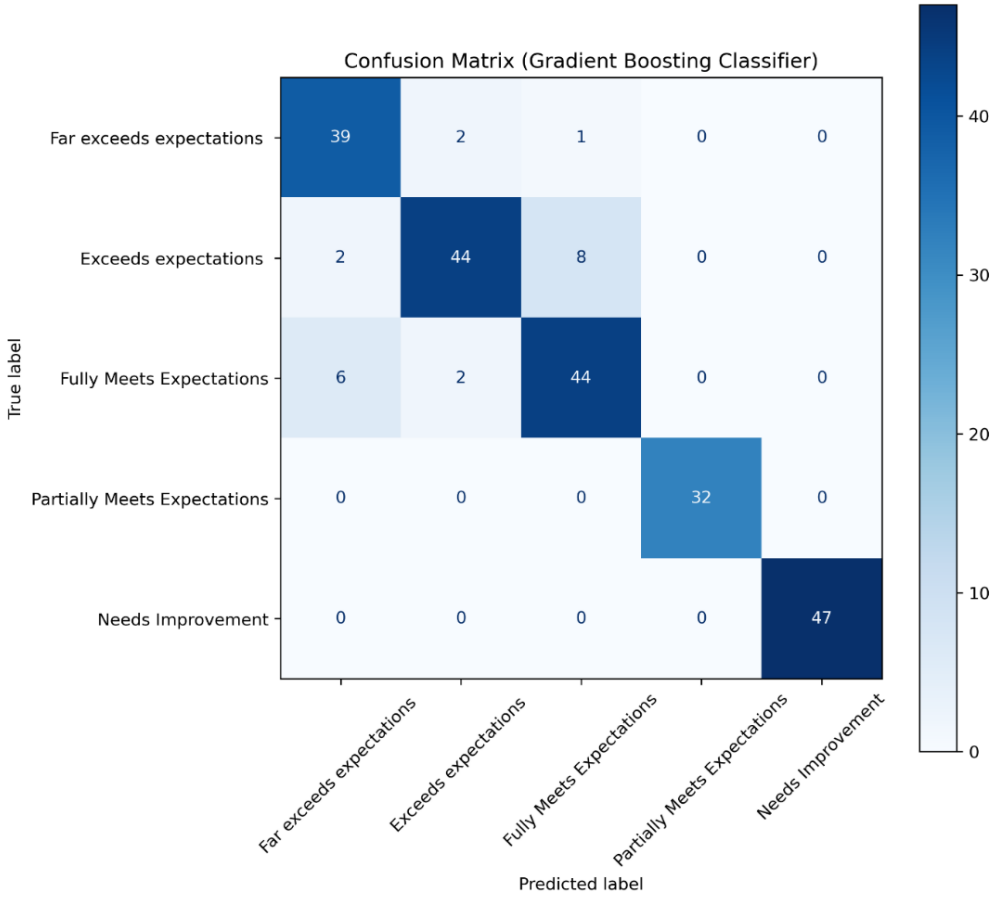


Figure 5.14 Gradient Boosting - Confusion Matrix

2. XGBoost

Similarly, XGBoost cleanly separates employees who Need Improvement or Partially Meet Expectations, with little to no confusion between these two groups and the remaining tiers. Minor misclassifications occur between Exceeds and Fully Meets expectations, and occasionally between Far Exceeds and a neighboring category. However, the majority of errors are small in number, illustrating XGBoost's effectiveness in differentiating employee performance levels—particularly at the lower end of the spectrum.

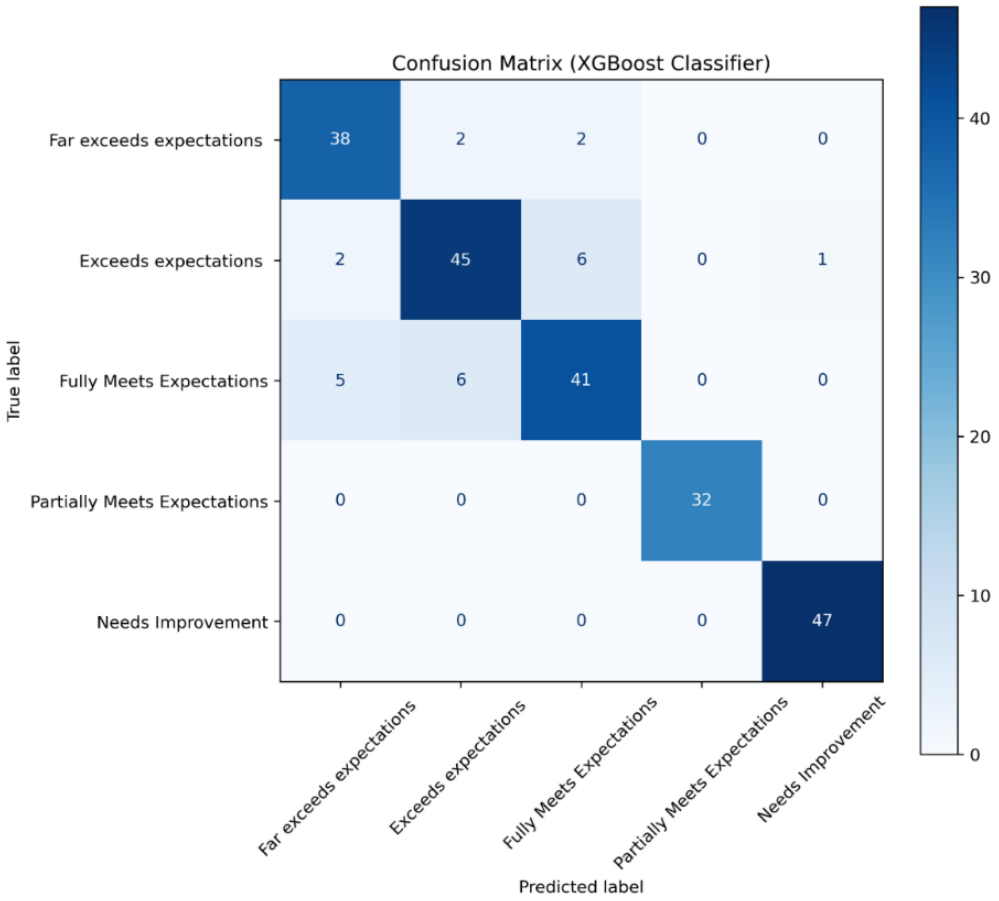


Figure 5.15: XGBoost - Confusion Matrix

3. Random Forest

   Random Forest also does a good job of identifying underperformers—Needs Improvement and Partially Meets Expectations— duplicating the other ensemble methods' performance. Several instances of Fully Meets being labeled as Exceeds, and vice versa, suggest a bit of bleed-over at the boundary of middle to high levels of performance. Random Forest rarely mistakes Far Exceeds Expectations for any substantially lower category, though, demonstrating good detection of top performers and good overall classification consistency.

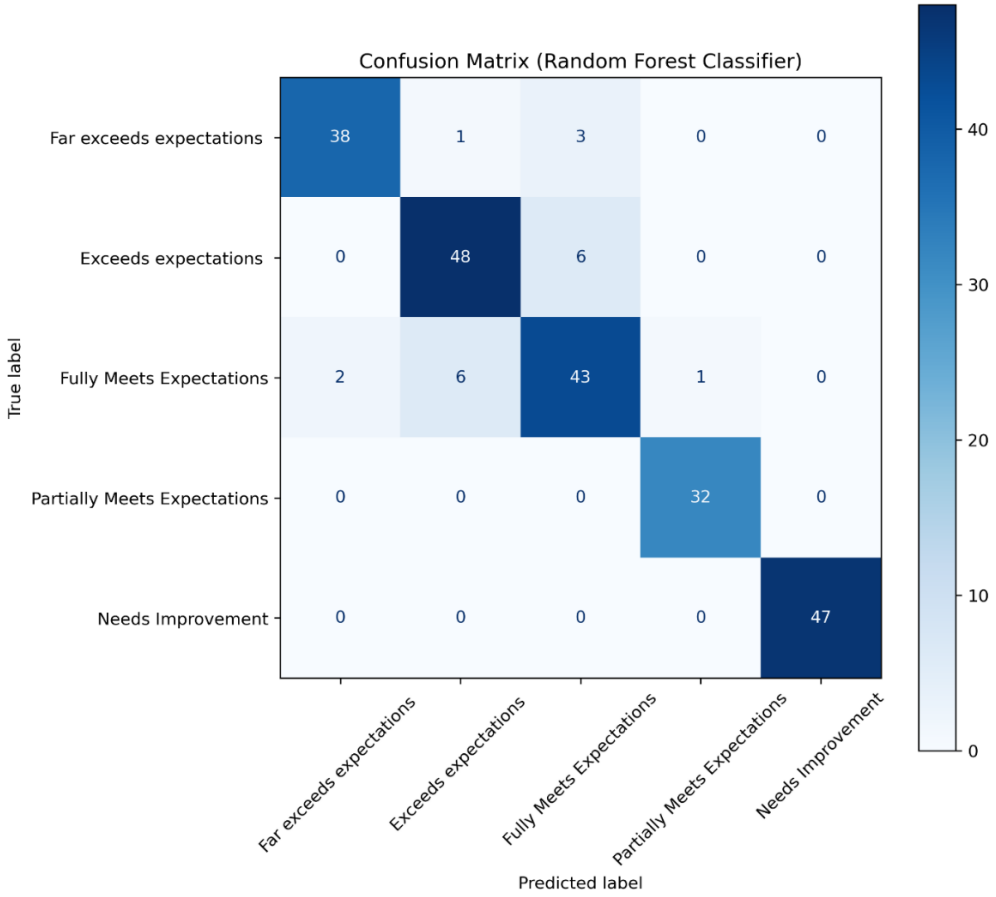


Figure 5.16: Random Forest - Confusion Matrix

4. K-Nearest Neighbors (KNN)

   KNN's confusion matrix indicates high accuracy for employees who need improvement or meet expectations to some degree, with no cases being misclassified into the higher range. Among the remaining categories, not many Fully Meets employees are misclassified as Far Exceeds, which indicates that distance-based metrics will occasionally lump high-scoring but not “far exceeding” individuals together. Notwithstanding these sporadic misclassifications, the K-Nearest Neighbors (KNN) algorithm exhibits high overall accuracy, especially for categories characterized by distinct boundaries.

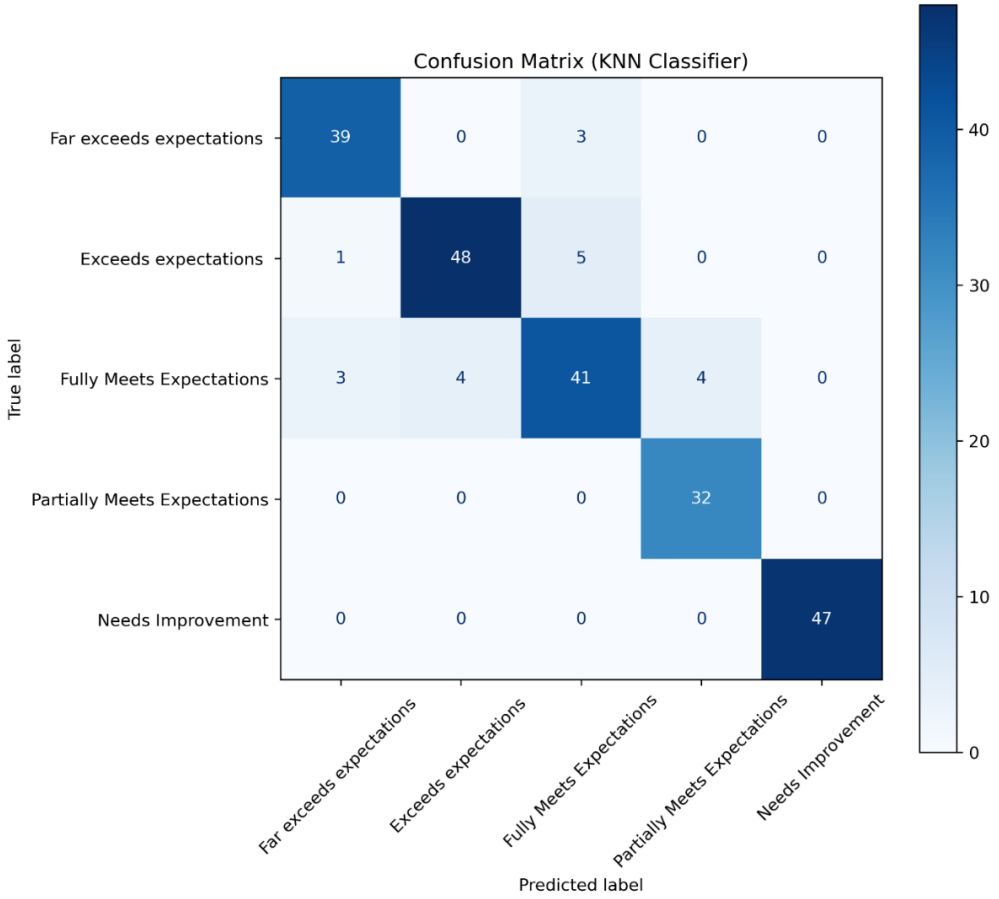


Figure 5.17: KNN - Confusion Matrix

5. Support Vector Machine (SVM)

   SVM reaffirms its leading performance with very few errors across all five categories. Both Needs Improvement and Partially Meets Expectations again approach flawless classification, and even among the high-performing tiers—Exceeds, Far Exceeds, and Fully Meets—misclassifications are minimal. Errors may occur when Fully Meets is classified as Exceeds or Far Exceeds, suggesting closely defined decision boundaries that could incorrectly categorize some borderline cases.

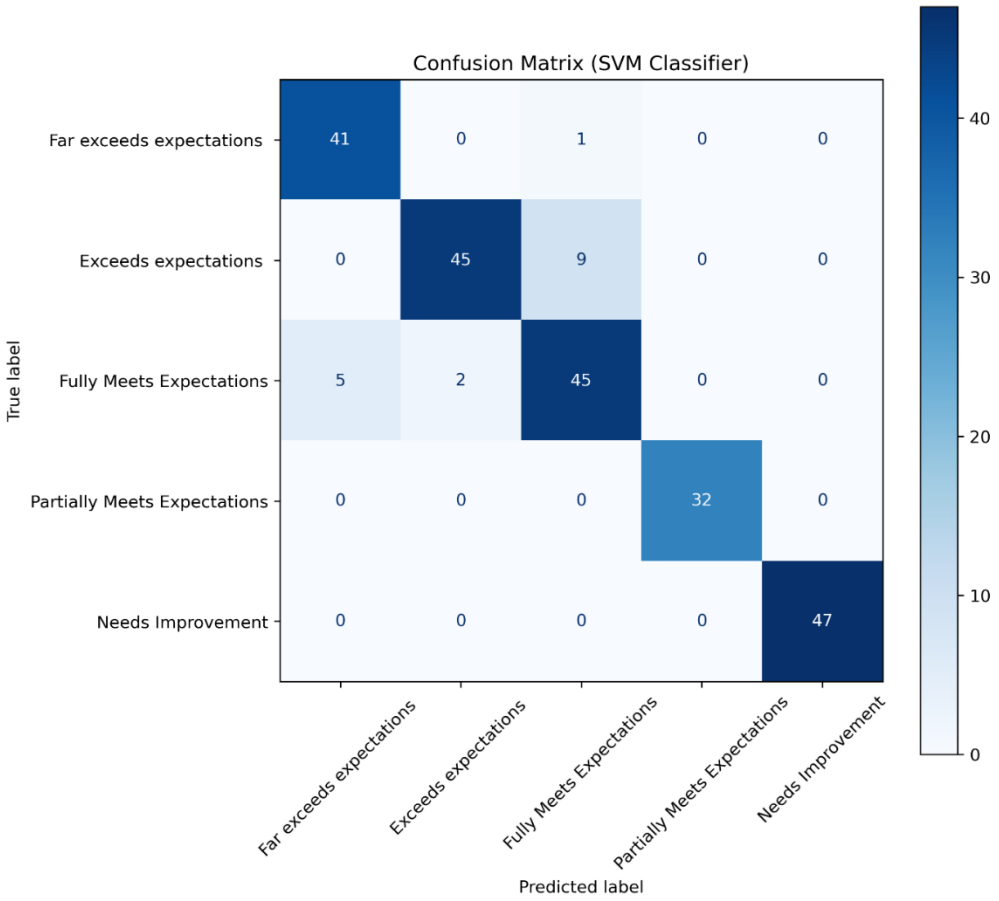


Figure 5.18: SVM- Confusion Matrix

Across all models, the largest proportion of misclassifications tends to occur between the higher performance classes (Exceeds, Far Exceeds, and Fully Meets Expectations). By contrast, the lower-performance tiers (Needs Improvement, Partially Meets Expectations) are consistently distinguished with very high accuracy, reflecting that the feature patterns differentiating these employees from others are especially clear. Nevertheless, the confusion matrices collectively illustrate that each model handles this complex multi-class task effectively, particularly when aided by the GA-selected feature subset and well-tuned hyperparameters.

5.6 Model Interpretability

5.6.1 Feature Importance Using Decision Tree

To interpret the factors influencing employee performance ratings, we utilized a Decision Tree Classifier, incorporating all available dataset features to quantify their relative importance. Unlike models such as linear regression or support vector machines (SVMs), decision trees provide a natural mechanism for evaluating feature importance, making them well-suited for explainable organizational analysis. This Decision Tree approach was selected for interpretability over predictive superiority, following best practices in explainable AI and organizational decision-making.

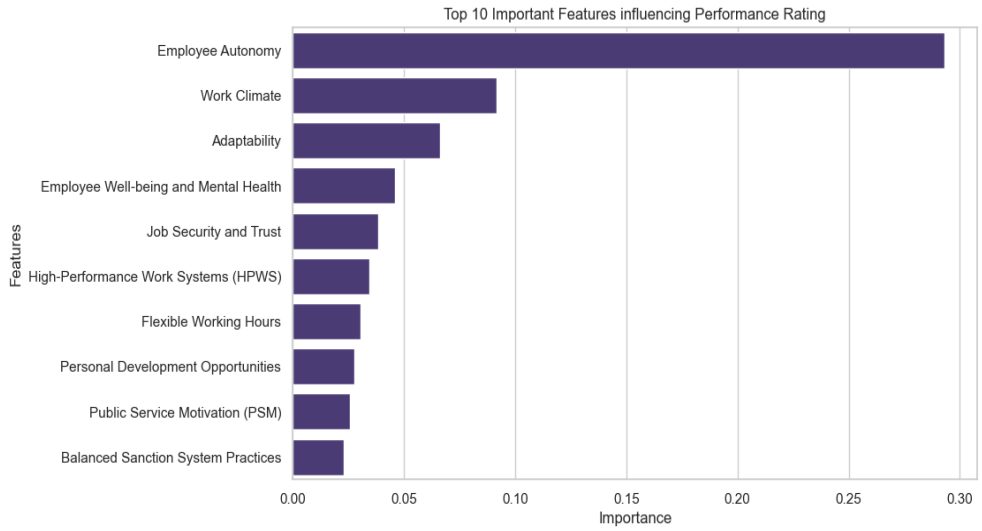


Figure 5.19: Top 10 Important Features Influencing Performance Rating

Figure 5.19 presents the top 10 most influential features affecting performance ratings, ranked by their importance scores. The findings offer some critical observations:

1. Employee Autonomy is the most predominant factor by a wide margin, overshadowing all others. This speaks volumes about the significance of autonomy in building motivation, engagement, and overall job performance. Employees with greater decision-making autonomy are

more likely to be satisfied and productive, which aligns with general organizational behaviour research.

2. Work Climate and Adaptability rank as the second and third most significant factors. A positive work climate promotes collaboration, psychological safety, and well-being, all of which are essential for high performance. On the other hand, adaptability reflects an employee's capacity to manage change and uncertainty, a valuable skill in evolving work environments.
3. Employee Well-being and Mental Health, Job Security and Trust, and High-Performance Work Systems (HPWS) highlight the importance of stability, support systems, and systematic processes in sustaining successful employee performance.
4. Flexible Working Hours and Personal Development Opportunities indicate that work structure and developmental opportunities significantly impact employee performance and motivation. Employees who can balance work and life and receive developmental opportunities perform better.
5. Public Service Motivation (PSM) and Balanced Sanction System Practices suggest that both intrinsic motivation and a just, structured discipline system are accountable for performance consistency and ethical conduct.

The results confirm established theoretical models, demonstrating that autonomy, adaptability, and a positive work environment are essential for building high-performing employees and teams. By prioritizing these discoveries, organizations can maximize workforce strategies, prioritize autonomy, improve the work environment, and provide structured employee support to drive long-term performance improvements.

5.6.2 Model Explanation Tools

Although the surrogate decision tree provides a useful macro-level perspective on feature importance, SHAP (SHapley Additive exPlanations) enables a more class-specific view of why certain employees fall into each performance category. Below, we present the SHAP findings for each tier, Exceeds Expectations, Far Exceeds Expectations, Fully Meets Expectations, Needs Improvement, and Partially Meets Expectations, based on the same decision-tree surrogate. This two-pronged interpretability strategy underscores which attributes most strongly sway the classifier's decisions for each performance level.

SHAP Analysis per Performance Class

1. Far Exceeds Expectations: For the highest echelon of performance, Adaptability (≈0.10) and Employee Autonomy (≈0.09) take center stage. This pattern implies that those who excel well beyond organizational targets tend to be both highly adaptable and granted considerable freedom in how they execute their responsibilities. HPWS, Employee Voice and Participation, Work Climate, and Flexible Working Hours each contribute moderately (≈0.04–0.05), highlighting that structured performance frameworks, open communication channels, and flexibility can further elevate employees from simply exceeding targets to far surpassing them.

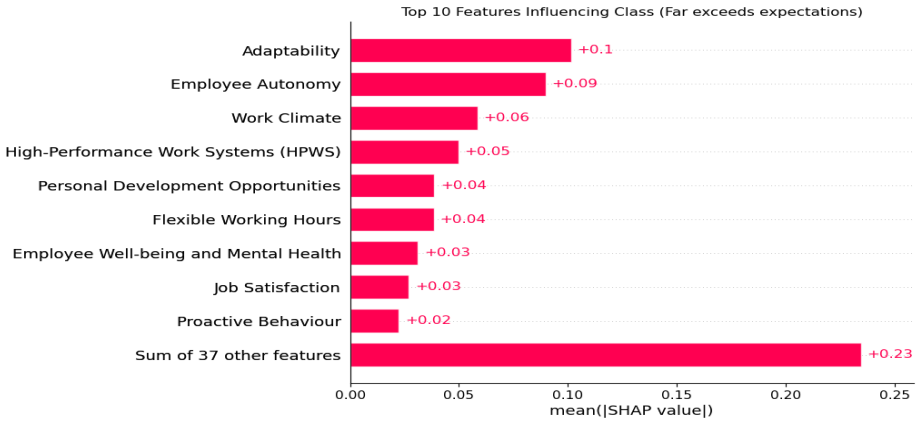


Figure 5.20: Top 10 Important Features Influencing Class (Far Exceeds Expectations)

2. Exceeds Expectations:

In this group, Employee Autonomy shows the largest mean SHAP value (≈0.09), suggesting that empowering employees to shape their own work is a key factor in surpassing standard expectations. Work Climate and Adaptability follow closely (≈0.06 each), underscoring that a supportive environment and the ability to handle change are likewise pivotal. High-Performance Work Systems (HPWS), Job Security and Trust, and Psychological Safety also emerge as notable, albeit somewhat smaller, influences, reflecting those structured systems, job stability, and a sense of interpersonal safety help employees consistently deliver above-average results.

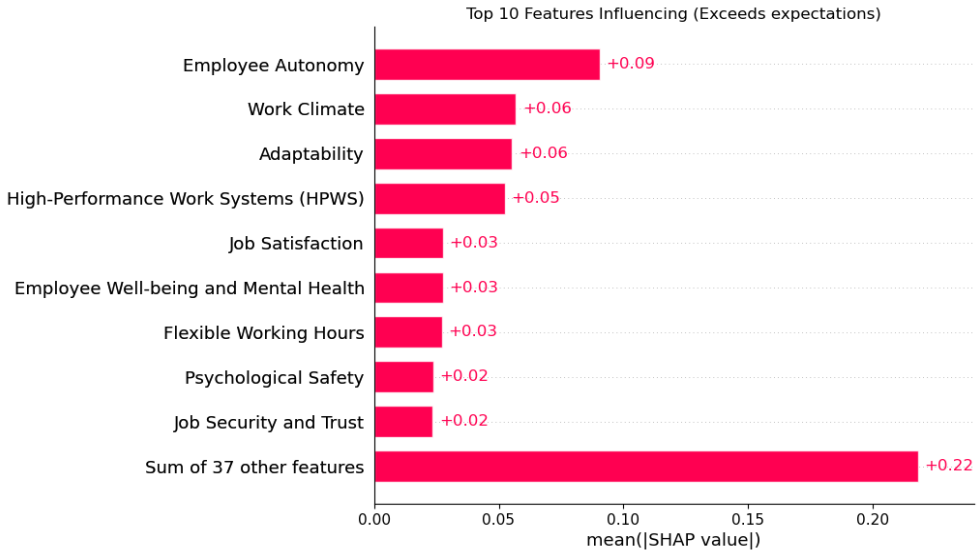


Figure 5.21: Top 10 Important Features Influencing Class (Exceeds Expectations)

3. Fully Meets Expectations

Among employees who fully meet expectations, Employee Autonomy remains the most influential factor (≈0.11), followed by Adaptability (≈0.07) and Work Climate (≈0.06). Notably, High-Performance Work Systems (HPWS) and Proactive Behavior (≈0.03 each) contribute to sustained performance, emphasizing the importance of structured processes and initiative-taking. Additionally, Employee Well-being and

Mental Health, Personal Development Opportunities, Job Security and Trust, and Flexible Working Hours (all ≈0.03) highlight the significance of stability, growth opportunities, and work-life balance in maintaining reliable performance levels. These insights reinforce the importance of a supportive and structured work environment in fostering consistent employee success.

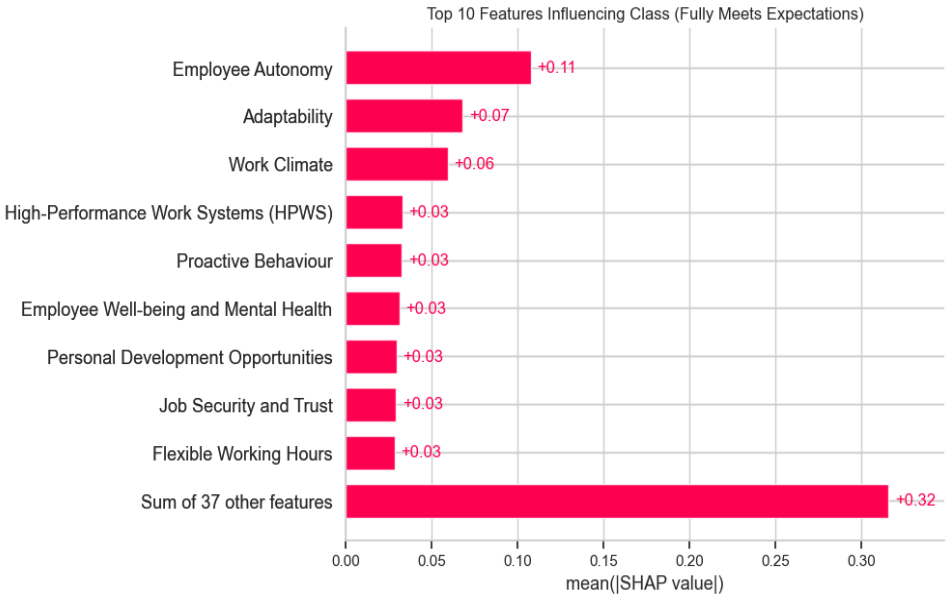


Figure 5.22: Top 10 Important Features Influencing Class (Fully Meets Expectations)

4. Partially Meets Expectations:

Employees who partially meet expectations show Adaptability (≈0.11) and Work Climate (≈0.10) as the most influential factors, followed by Employee Autonomy (≈0.08). This suggests that while some degree of independence and a supportive work environment contribute to their performance, gaps in adaptability or workplace climate may prevent them from fully excelling. Additionally, Technological Integration and Competence, Job Security and Trust, and Organizational Structure and Clarity (≈0.03 each) indicate that well-defined structures, stability, and technological competence could help bridge the performance gap. Furthermore, Performance Appraisal Mechanisms, Competence, and Public Service Motivation (PSM) (≈0.02 each) highlight the role of

structured feedback, individual capability, and intrinsic motivation in enhancing employee outcomes. Addressing these areas could support employees in progressing toward fully meeting expectations.

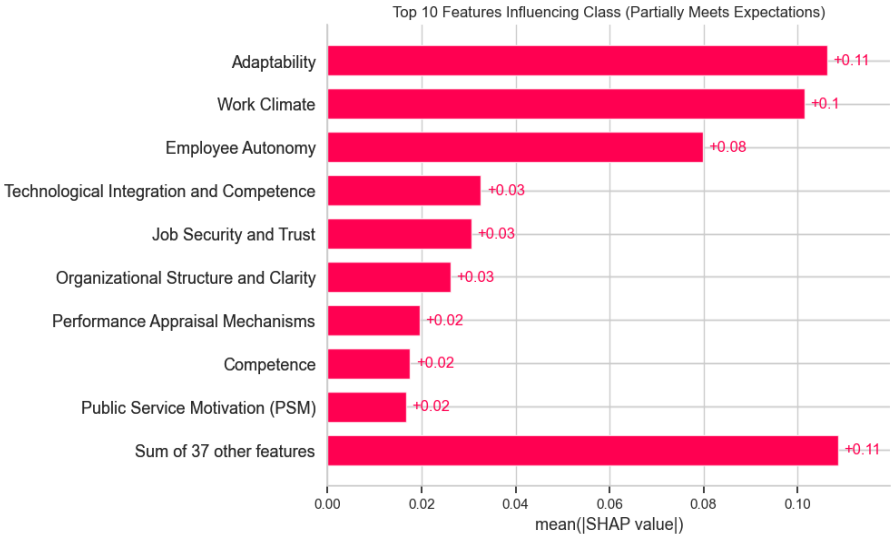


Figure 5.23: Top 10 Important Features Influencing (Partially Meets Expectations)

5. Needs Improvement

A dramatic pattern emerges in this group, Employee Autonomy features a dominant SHAP value (≈0.30), towering over all other features. This means that a lack of autonomy, or a mismatch between autonomy and support needs, very strongly correlates with underperformance. Job Security and Trust (≈0.03) is the only other factor with a tangible impact, reinforcing that stability concerns can contribute to poorer performance. Conversely, other factors such as Digital Literacy and Skills, Job Satisfaction, Employee Well-being and Mental Health, and Change Management score close to zero, indicating they have little contribution in this cohort. Together, the numbers suggest that low autonomy and job security concerns are the primary drivers for employees falling into the "Needs Improvement" group. Addressing these shortcomings could be critical in improving overall performance.

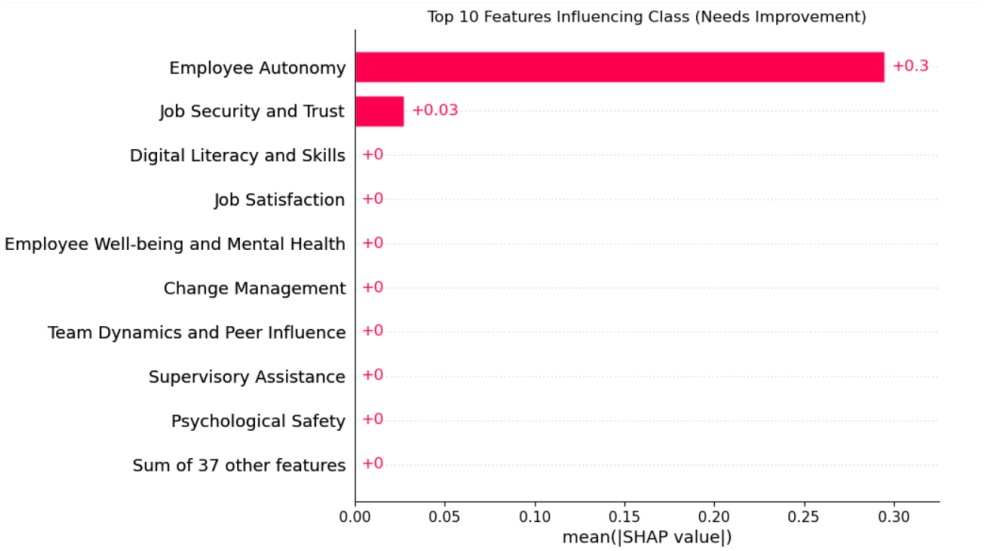


Figure 5.24: Top 10 Important Features Influencing (Needs Improvement))

While the decision-tree surrogate cannot perfectly replicate the complex decision boundaries inherent in more advanced classifiers, the SHAP analyses still align closely with well-established principles in organizational behavior. Across the higher-performing categories, Employee Autonomy consistently stands out as a top driver, accompanied by influential factors such as Adaptability, Work Climate, and High-Performance Work Systems (HPWS). In lower-performing tiers, significant deficits in autonomy or trust appear particularly correlated with underperformance.

5.7 Ethical Considerations in Applying AI and Machine Learning

The application of artificial intelligence (AI) and machine learning (ML) in predicting workers' performance and enhancing organizational decision-making holds excellent potential for efficiency and accuracy. However, it is imperative to acknowledge the ethical concerns that accompany these technological advancements, most notably bias, transparency, accountability, and data privacy issues. Even though explainable AI (XAI) has, to a certain extent, overcome the so-called "black box" issue through interpretability in machine learning models (Angelov et al., 2021; Holzinger et al., 2020), there are still significant ethical concerns (Doshi-Velez and Kim, 2017; Rudin, 2019). These concerns require strong approaches to promote fairness, trust, and participatory decision-making at all organizational levels.

1. Algorithmic Bias and Fairness:

A significant concern in the realm of AI-driven employee performance prediction pertains to the presence of algorithmic bias. The training of machine learning (ML) algorithms with historical data can, in certain circumstances, be influenced by societal and organizational biases, thereby leading to biased predictions (Barocas et al., 2016). The impact of biased predictions on employees' performance can disproportionately affect specific groups, thereby exacerbating workplace inequity (Angelov et al., 2021). To address these concerns, researchers and practitioners have proposed using fairness-aware ML methodologies, implementing algorithm audits, and continuously monitoring models (Nayem and Uddin, 2024).

2. Confidentiality and Security of Data:

High-performance AI and machine learning (ML) algorithms typically rely on extensive individual and occupational data, including performance metrics, behavioural patterns, and demographic information (Mittelstadt et al., 2016). Protecting information entails more than merely excluding unauthorized access; it also involves adherence to regulatory frameworks (e.g. GDPR, CCPA) that impose stringent requirements for collecting, storing, and distributing information. Implementing secure encryption protocols, secure information-handling processes, and transparent consent policies is imperative to foster workers' trust and confidence in AI-powered performance management (Iqbal and Guibas, 2024).

3. Transparency and Trust

It is important to note that AI can occasionally be delivered in a "black box" format, and both workers and decision-makers can have a problem with seeing how forecasts and evaluations are generated (Holzinger et al., 2020). XAI tools, such as LIME or SHAP, can deliver valuable interpretability. Still, it is worth providing ongoing training for workers regarding the purpose of the AI system, its restrictions, and its nature (Chandra et al., 2023). The provision of transparent justifications for decisions and the opportunity for workers to challenge AI evaluations fosters an environment characterized by transparency, accountability, and respect (Nayem and Uddin, 2024).

4. AI-Human Collaboration

It is essential to note that AI is not intended to replace human discretion but rather to augment it. In a model with a human in the loop, HR and group leaders make the final decision, guided by insights from machine learning (Iqbal and Guibas, 2024). Integrating human empathy, contextual awareness, and moral logic in performance assessments and organizational decisions fosters balanced and fair practice. Ideally, AI predictive

capabilities identify trends or warnings early on, and then human professionals validate such observations, interpret contextual factors, and tailor interventions to individual cases (Makridakis et al., 2018).

5. Workplace Dynamics and Employee Autonomy

The application of AI in the context of performance monitoring and evaluation in the workplace can, in a passive manner, engender a state of perpetual observation, potentially harming employee morale and autonomy. Workers' reactions are characterized by a duality of concerns, encompassing apprehensions regarding punitive actions and biases inherent in machine-generated feedback (Angelov et al., 2021). Organizations must, therefore, convey positive objectives for AI implementations, such as personalized coaching or talent development, and reduce overreaching observation methodologies. Transparent governance and information use policies conducive to transparency engender a favourable work environment.

The application of AI and ML in workforce forecasting and performance evaluation holds considerable potential for workforce and organizational development. However, it is essential to note that the ethical use of AI will rely on transparency, fairness, and a balanced proportion between algorithm and human discretion. Explainable AI (XAI) has been identified as a mechanism for overcoming such apprehensions through transparency in decision-making, identifying bias, and enhancing trust. In the future, organizations will be required to establish explicit protocols, robust security protocols for information, and participative governance frameworks in order to ensure that AI-enabled performance output is logical, fair, and in harmony with organizational values. With such interventions, AI and machine learning (ML) are anticipated to become powerful adjuncts to human expertise, contributing towards a fairer and more effective performance management model in the workforce.

5.8 Summary

This chapter presents the empirical findings from expert interviews and data analysis, which have been used to identify key factors that influence employee performance in Bahrain's public sector. The study has refined an initial list of 54 factors, consolidating and modifying them based on expert insights and supporting literature. The newly introduced factors encompass Performance Appraisal Mechanisms, Job Security and Trust, Balanced Sanction System Practices, Hybrid Work Models, and Commute and Accessibility, reflecting contemporary workplace trends such as flexible work arrangements and the impact of urban infrastructure on productivity. Additionally, redundant factors were merged, such as integrating various training and development aspects into a broader Employee Development category. A correlation analysis revealed strong relationships between several key factors and employee performance. A strong correlation was identified between Public Service Motivation (PSM) and Knowledge-Sharing Ability and Communication Skills, indicating that intrinsically motivated employees were more likely to engage in collaboration. A high correlation was also identified between Organizational Citizenship Behaviours and Proactive Behavior, suggesting that employees who exceeded job expectations often contributed to workplace improvements. A strong correlation was identified between High-Performance Work Systems (HPWS) and an Agility and Innovation Culture, emphasizing that structured, well-supported work environments fostered adaptability and creativity.

The Genetic Algorithm (GA) was employed to refine feature selection, identifying the most impactful factors for predictive modeling.Machine learning models, including XGBoost, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), were evaluated for classification accuracy. SVM emerged as the top-performing

model, achieving 92.51% accuracy, while all models demonstrated strong predictive capabilities, particularly in distinguishing between high- and low-performing employees. The SHAP (SHapley Additive Explanations) values and a Decision Tree Classifier were used to interpret feature importance, revealing that Employee Autonomy, Work Climate, Adaptability, and Psychological Safety were the most significant factors influencing employee performance.

Finally, the chapter discussed ethical considerations in AI-driven employee performance assessment, including bias, transparency, data privacy, and workplace autonomy, and emphasized the importance of balancing AI predictions with human oversight and contextual judgment to ensure fairness and effectiveness. These findings provided actionable insights for enhancing workforce policies and optimizing employee performance management in Bahrain's public sector.

Chapter 6
Conclusion, Recommendations and Future Work

6.1 Conclusion

The present thesis proposes a novel paradigm for employee performance management, postulating the integration of AI-driven predictive models with advanced machine learning and genetic algorithms as a means not only to meet but also to surpass the objectives of extant research in this field. The study identified 54 potential performance drivers from the extant literature, which were refined to 46 key determinants in the Bahraini public sector through expert interviews and focus group discussions. This meticulous refinement process addresses the first research question (RQ1) and satisfies the corresponding objective (RO1) by ensuring that the performance factors are both context-specific to the Bahraini public sector and aligned with established theoretical frameworks. Developing a robust, adaptive system transformed traditional performance appraisals into a dynamic, continuous process. The employment of models such as Support Vector Machines (SVM), which attained an impressive accuracy of 92.51%, serves to confirm that the predictive framework effectively forecasts employee outcomes, thereby fulfilling the second research question (RQ2) and its associated objectives (RO2 and RO3). The application of genetic algorithms further enhanced the model's predictive performance by rigorously selecting and consolidating features, including novel, context-specific factors such as Performance Appraisal Mechanisms and Hybrid Work Models.

In addition to its predictive component, the thesis thoroughly explores AI-assisted decision-making frameworks, encompassing ROC analyses, confusion matrix evaluations, and interpretability assessments using decision trees and SHAP values. This exploration addresses the third research question (RQ3) and supports the objective of providing practical, data-driven HR interventions (RO4). The employment of sophisticated analytical techniques, in conjunction with expert insights, has been demonstrated to reliably capture the nuanced realities of Bahrain's public sector, thereby reinforcing the significance of factors such as employee autonomy, work climate, and adaptability. The study also placed ethical considerations at the centre of its framework, ensuring that the implementation of AI in performance management remains fair, transparent, and secure. The thesis critically examined issues related to bias, data security, and transparency, thereby addressing the fourth research question (RQ4) and meeting the objective of integrating responsible and ethical AI practices into performance management (RO5). Thus, the empirical findings confirm that the research objectives have been comprehensively met.

Integrating expert insights with sophisticated machine learning techniques validates the study's methodological framework and paves the way for more adaptive, transparent, and robust performance management strategies in the public sector. By aligning these advanced AI applications with Bahrain's unique socio-cultural and organizational dynamics, the thesis contributes significantly to both the academic discourse and practical applications in human resource management. The integrated approach enhances operational effectiveness and supports informed, ethical decision-making, thereby fostering a sustainable, data-driven framework for organizational success.

6.2 Study's Recommendations

This research aimed at improving employee performance management in Bahrain's public sector through AI-based predictive and decision-making models. The following targeted recommendations directly align with the research findings, achieving the research objectives:

1. Ethical Implementation and AI Governance
    - Develop clear AI Ethics Policies emphasizing transparency, fairness, and accountability in using predictive models to ensure employee trust and minimize bias.
    - Maintain Human Oversight to use AI insights for decision-support, not automated decisions, ensuring human judgment and contextual understanding are retained.
2. Technology Integration and Data Infrastructure
    - Adopt the Validated Predictive Models, gradually integrating it into government HR systems to forecast performance and identify improvement areas.
    - Implement Explainable AI (XAI) tools (e.g., SHAP) to clearly communicate AI decisions to managers, linking performance predictions directly to employee-specific factors identified in the findings.
3. Leveraging AI Insights in Human Resource Policies and Procedures
    - Revise HR Performance Management Policies to explicitly incorporate AI-based insights into regular evaluations, thereby enhancing objectivity and meritocracy, aligning with the identified key performance drivers (e.g., autonomy, adaptability, psychological safety).
    - Transition to Continuous Performance Monitoring facilitated by AI analytics, replacing annual reviews with more frequent, data-informed feedback loops, directly addressing real-time performance gaps identified by the predictive models.
4. Capacity Building and Change Management

- Conduct AI Literacy and Ethics Training for HR and executives' staff to ensure effective use of AI tools and a clear understanding of AI-based decision-making.
- Implement Change Management Initiatives (pilots, workshops, change champions) to encourage buy-in and address employee concerns proactively, aligning AI adoption with practical needs.

5. Strategic Alignment with Digital Transformation
   - Integrate AI Performance Management Initiatives into broader national strategies such as Bahrain's Vision 2030 and Updates for 2050, emphasizing efficiency, innovation, and a high-performance organizational culture.
   - Secure Senior-Level Sponsorship and Continuous Evaluation by establishing a central oversight authority, ensuring consistent standards, scalability, and periodic assessment of the AI-driven approach to maintain relevance and accuracy.

These practical, and research-linked recommendations provide a realistic framework for successfully enhancing employee performance management through AI in Bahrain's public sector.

6.3 Future Work

Future work must capitalize on these findings by employing longer-time-scale longitudinal study designs. In this way, dynamic trends will emerge, and increased insight will be gained into predictive models' performance as organizational contexts shift. Exploring further the application across an expanded range of contexts in both the public and private sectors will also permit us to gauge whether these AI models are transferable and scalable. Furthermore, governance processes must be developed to enhance ethical management, increase transparency in AI systems, address potential biases, and ensure ongoing accountability in decision-making.

An avenue for future research is to examine the model's transferability across the GCC region. Adapting the predictive framework for neighboring Arabian Gulf states (e.g., Oman, Saudi Arabia, Qatar, Kuwait and the UAE) would necessitate retraining the models using each country's specific public-sector employee datasets and tailoring the implementation to align with local legal frameworks and civil service regulations, such as Oman's civil service laws. Prior research indicates that predictive models often lose accuracy when applied outside their original context, thus necessitating recalibration and validation with local data (Hand, 2006). Additionally, comparative analyses of AI governance in the GCC highlight that aligning AI-driven initiatives with local policy environments and legal standards is crucial for ensuring responsible and effective adoption. Addressing these regional adaptations explicitly in future implementations would enhance the model's robustness and facilitate generalizability across diverse public sector environments within the GCC.

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Appendices

Appendix (A) Expert Interview Guide

مقابلات مع خبراء لتنقيح العوامل المؤثرة على أداء الموظفين في القطاع العام البحريني

Interviews with Experts to Refine the Factors Influencing Employee Performance in the Bahraini Public Sector

هذه الدراسة هي جزء مميد لسلسلة من الإجراءات المنهجية المقترحة لأطروحة الدكتوراة في مجال تحليل الأعمال تحت عنوان " تعزيز إدارة أداء الموظفين من خلال نماذج تنبؤية وصنع القرار مدعومة بالذكاء الاصطناعي ".

يهدف هذه الدراسة إلى اكتساب فهم أعمق للعوامل المؤثرة على أداء الموظفين في القطاع العام البحريني. ولتحقيق ذلك، وبصفتكم خبيراً مشهوداً لكم في مجال الإدارة والقيادة، سأعرض عليكم مجموعة مكونة من 54 عاملاً من العوامل المؤثرة في أداء الموظفين، والتي أستخلصها الباحث من مراجعة الأدبيات (تضم أكثر من 60 مصدراً). وهي موضحة في المرفق باللغتين العربية والإنجليزية. يُرجى منكم التفكير في مدى انطباق هذه العوامل على القطاع العام البحريني وتحديد أي منها، إن وجدت، مناسب لاستقصاءها من موظفي القطاع العام تمهيداً لقياسها ميدانياً من خلال أداة الاستبيان. بالإضافة إلى ذلك، قد ترغبون في النظر في إدراج عوامل أخرى مؤثرة على أداء الموظفين في القطاع العام البحريني قد تكون غير مدرجة في قائمتنا المرفقة.

يرجى ملاحظة أنه سيتم التعامل مع أي معلومات شخصية مقدمة بسرية تامة. لا يُسمح بمشاركة هذا المستند أو الرابط مع الآخرين، حيث إن هذه الدراسة مقتصرة على خبراء في المجال الأكاديمي أو الإداري تم اختيارهم بعناية وبشروط محددة.

This study represents the preliminary phase of a series of methodological procedures proposed for a PhD thesis in Business Analysis. The thesis is entitled "Enhancing Employee Performance Management through AI-enabled Predictive and Decision-Making Models."

The objective of this study is to gain a deeper understanding of the factors influencing employee performance in the Bahraini public sector. To achieve this, we have conducted interviews with experts in the field. As a recognized expert in the field of management and leadership, you will be presented with a set of 54 factors extracted by the researcher from the literature review (> 60 sources). These factors influence employee performance and are presented in attachments in both Arabic and English. It is recommended that you consider the applicability of these factors to the Bahraini public sector and determine which, if any, are appropriate to survey public sector employees in preparation for measuring them in the field through the questionnaire. In addition, you may wish to consider including any missing factors.

Please be advised that any personal information provided will be treated in strict confidence. Please note that this document or link may not be shared with others. This study is restricted to carefully selected academic or administrative experts under specific conditions.

Name (optional): ..... Current or previous position: .....

Years of experience in management: ..... Academic qualification: .....

Factors Affecting Employee Performance	ملاءمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Public Service Motivation (PSM):			**الدافع للخدمة العامة:**
This way, it attempts to improve the workers' performance, especially those in public sector organizations. Here, the motivating factor is the desire to serve the public and contribute positively to society (Sudha et al., 2023; Perry & Wise, 1990).			يحاول هذه الطريقة تحسين أداء العاملين، خاصة العاملين في مؤسسات القطاع العام. والعامل المحفز هنا هو الرغبة في خدمة الجمهور والمساهمة بشكل إيجابي في المجتمع.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Knowledge Sharing Ability:			**القدرة على مشاركة المعرفة:**
This would play a significant role in the performance of employees. Sharing and using knowledge efficiently within any organization requires the cultivation of both learning and innovation, which, in turn, results in improved performance outcomes (Kim & Lee, 2006).			تلعب دورًا هامًا في أداء الموظفين عالقدرة على تبادل المعارف والاستفادة منها بفعالية داخل المنظمة تعزز بيئة التعلم والابتكار، مما يؤدي إلى تحسين نتائج الأداء.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Job Satisfaction and Loyalty:			**الرضا الوظيفي والولاء:**
It is evident that job satisfaction and loyalty are fundamental to the attainment of superior employee performance. It can be reasonably assumed that satisfied and loyal employees will be associated with higher levels of commitment and productivity within their respective organizations (Yurdakalmaz et al., 2011).			مما هميول في الحفاظ على مستويات عالية من أداء الموظفين. فالموظفون الذين يشعرون بالرضا والولاء، فلوسيم من المرجح أن يظهروا مستويات أعلى من الالتزام والإنتاجية.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Emotional Intelligence (EI):			**الذكاء العاطفي:**
It is comprising abilities such as self-awareness, self-regulation, motivation, empathy, and social skills, significantly affects how employees interact with their peers and manage stress and challenges at work (Khan et al., 2017).			يلعب دورًا هامًا في أداء الموظفين. فالموظفون الذين يتمتعون بمستويات عالية من الرضا الوظيفي والولاء، فلوسيم من المرجح أن يظهروا مستويات أعلى من الالتزام والإنتاجية. ويتوافق الذكاء العاطفي، والذي يتضمن قدرات مثل الوعي الذاتي، والتنظيم الذاتي، والتحفيز، والتعاطف، والمهارات الاجتماعية، ويؤثر بشكل كبير على كيفية تفاعل الموظفين مع أقرانهم وإدارة الضغوط والتحديات في العمل.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Cognitive Abilities and Problem-Solving:			**القدرات المعرفية وحل المشكلات:**
These are necessary for dealing with complex information processing and problem-solving, hence highly important for effective work performance. An employee with high cognitive ability is likely to effectively and efficiently undertake his tasks (Otero et al., 2021).			في هذراد ضرورية لمعالجة المعلومات وحل المشكلات المعقدة. وبالتالي تلعب دورًا محوريًا في أداء الموظفين. ويمكن للموظفين ذوي القدرات المعرفية العالية أداء المهام بكفاءة وفعالية أكبر.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملاءمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Organizational Citizenship Behaviors (OCBs):			**سلوكيات المواطنة التنظيمية:**
They include voluntary and extra-role behaviors and contribute significantly to the overall performance of the organization. These behaviors improve the social and psychological environment of the workplace, thereby enhancing collective productivity (Gaur & Frenkel, 2018).			تشمل السلوكيات التطوعية والخارجة عن الأدوار، وتساهم بشكل كبير في الأداء العام للمؤسسة. تعمل هذه السلوكيات على تحسين البيئة الاجتماعية والنفسية للمكان العمل، مما يعزز بالتالي الإنتاجية الجماعية.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Adaptability:			**القدرة على التكيف:**
This is important in workplaces to ensure employees can work with changes and uncertainties. Adaptable workers are awarded for positive responses toward changes in the work environment and working demands, which significantly affect the individual performance of the employees (Peng et al., 2021).			إن القدرة على التكيف، في مكان العمل أمر بالغ الأهمية للتكيف مع التغيير وعدم اليقين. فالموظفون الذين يتسمون بالقدرة على التكيف يكونون أكثر قدرة على الاستجابة للتغييرات وبيئات العمل المتغيرة، مما يؤثر إيجاباً على أدائهم.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Proactive Behavior:			**السلوك الاستباقي:**
This is related to the initiative and change orientation of an employee. The definition of foresight encompasses the ability to identify potential issues, needs, or changes in the future and to take precautionary steps to address them in a way that ultimately leads to favorable performance outcomes (Peng et al., 2021).			يرتبط هذا السلوك بالمبادرة الموظفين للمبادرة والتوجه نحو التغيير. ويتضمن هذا السلوك توقع المشاكل أو الاحتياجات أو التغييرات المستقبلية والتصرف وفقًا لتلك التوقعات، مما يؤدي إلى نتائج أداء أفضل.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Competence:			**الكفاءة:**
The skills, knowledge and abilities required for the effective execution of job tasks are regarded as some of the most significant determinants of employee performance. It can be reasonably assumed that competent employees in their respective fields are likely to be high performers in terms of their job responsibilities (Mahmood et al., 2018).			تعتبر المهارات والمعارف والقدرات المطلوبة لتنفيذ الفعال للمهام الوظيفية من أهم محددات أداء الموظف. يمكن الافتراض بشكل معقول أن الموظفين الأكفاء في مجالاتهم التخصصية من المرجح أن يكونوا ذوي أداء عالٍ فيما يتعلق بمسؤولياتهم الوظيفية.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملاءمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Communication Skills:			**مهارات الاتصال:**
These are a requirement for ensuring the proper information flow and working together in a good work setting, which is essential for the high performance of employees (Gökkaya & Erez, 2020).			هذه المهارات أساسية في ضمان التدفق الفعال للمعلومات والتعاون والحفاظ على بيئة عمل إيجابية. وتُعد أمور ضرورية لتحقيق أداء عالٍ للموظفين.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Leadership Style:			**أسلوب القيادة:**
The leadership style adopted by the organization plays a vital role in the performance of the organization's employees. The leadership styles that exist in the organization include transformational, transactional, and laissez-faire, among other styles, can bear varied effects on employee motivation and satisfaction respectively, which will be felt in their overall performance in the organization (Hajjali et al., 2022; Mirgawati et al., 2022).			يلعب أسلوب القيادة الذي تتبناه المنظمة دورًا حيويًا في أداء موظفي المنظمة. تشمل أساليب القيادة الموجودة في المنظمة أساليب القيادة التحويلية والمعاملاتية وعدم التدخل، وهي من الأساليب الأخرى، والتي يمكن أن تحمل تأثيرات متنوعة على تحفيز الموظفين ورضاهم عن الأساليب الأخرى، والتي يمكن أن تحمل تأثيرات متنوعة على تحفيز الموظفين ورضاهم على التوالي، وهو ما سينعكس على أدائهم العام في المنظمة.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Organizational Culture:			**الثقافة التنظيمية:**
The issue is significantly relevant to employee performance. A positive and supportive organizational culture has been demonstrated to enhance employees' motivation and job satisfaction, thereby improving their performance (Putra et al., 2019; Ibrahim et al., 2022).			يرتبط هذه المسألة بشكل كبير بأداء الموظفين. وقد تمت أن الثقافة التنظيمية الإيجابية والداعمة تعزز من تحفيز الموظفين ورضاهم الوظيفي، وبالتالي تحسين أدائهم.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Work Climate:			**مناخ العمل:**
This has a considerable impact on an employee's well-being and performance. A positive work environment is associated with high levels of job satisfaction, motivation, and performance among employees at their place of work (Kinuthia et al., 2021; Winokan et al., 2022).			يمارس مناخ العمل تأثيرًا كبيرًا على رفاهية الموظفين وأدائهم. ويرتبط مناخ العمل الإيجابي بمستويات أعلى من الرضا الوظيفي والتحفيز والأداء.
If/when indicating 'No', please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمة للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Work-Life Balance:			**التوازن بين العمل والحياة:**
The concept of work-life balance is increasingly being recognized as a critical factor influencing employee performance. A healthy balance between work and personal life is essential for reducing stress and preventing burnout, which in turn leads to improved job satisfaction and productivity (Greenhaus & Beutell, 1985; Rustiaman et al., 2020).			يتزايد الاعتراف بمفهوم التوازن بين العمل والحياة الشخصية كعامل حاسم يؤثر على أداء الموظفين. يُعد التوازن الصحي بين العمل والحياة الشخصية أمرًا ضروريًا للحد من الإجهاد ومنع الإرهاق، مما يؤدي بدوره إلى تحسين الرضا الوظيفي والإنتاجية.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Technological Advancement:			**التقدم التكنولوجي:**
The introduction of new technologies within the workplace has a significant impact on employee performance. The implementation of contemporary technology can facilitate the optimization of processes, facilitate communication, and facilitate the more efficient completion of tasks, thereby enhancing overall performance (Beesankar et al., 2002).			يؤثر إدخال التكنولوجيات الجديدة في مكان العمل تأثيرًا كبيرًا على أداء الموظفين. ويمكن أن يؤدي تطبيق التكنولوجيا الحديثة إلى تبسيط العمليات، وتسهيل التواصل، وتيسير إنجاز المهام بكفاءة أكبر، وبالتالي تعزيز الأداء العام.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Empowerment:			**تمكين الموظف:**
It refers to the degree of freedom and independence an employee has in their job. There is a positive correlation between autonomy and job satisfaction, creativity, and performance. Employees who feel more empowered and responsible for their work tend to be more satisfied with their jobs and perform better. (Bhilwar et al., 2019)			يشير إلى درجة الحرية والاستقلالية التي يمتع بها الموظف في وظيفته. هناك علاقة إيجابية بين الاستقلالية والرضا الوظيفي والإبداع والأداء. يميل الموظفون الذين يشعرون بمزيد من التمكين والمسؤولية عن عملهم إلى أن يكونوا أكثر رضا عن وظائفهم ويحققون أداءً أفضل.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Training and Development Opportunities:			**فرص التدريب والتطوير:**
Training and development opportunities play a pivotal role in employee performance. Continuous learning and skill development are essential for adapting to changing job requirements and technologies, which in turn enhances job competence and performance (Saputri et al., 2020).			تلعب فرص التدريب والتطوير دورًا محوريًا في أداء الموظفين. فالتعلم المستمر وتطوير المهارات ضروريان للتكيف مع المتطلبات الوظيفية والتكنولوجيات المتغيرة، وهذا بدوره يعزز الكفاءة والأداء الوظيفي.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمة للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
High-Performance Work Systems (HPWS):			**أنظمة العمل عالية الأداء:**
They are sets of human resource practices that are designed to enhance employee capabilities and motivation, which in turn leads to high organizational performance. HPWS can positively affect employee resilience, engagement, and overall job performance (Gianetkis et al., 2019; Cooke et al., 2019).			في مجموعات من ممارسات الموارد البشرية المصممة لتعزيز قدرات الموظفين وتحفيزهم، مما يؤدي بدوره إلى أداء تنظيمي عالٍ. يمكن أن تؤثر أنظمة العمل عالية الأداء بشكل إيجابي على مرونة الموظفين ومشاركتهم وأدائهم الوظيفي بشكل عام.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Engagement:			**اندماج الموظفين:**
Employee engagement is a significant predictor of employee performance. Engaged employees demonstrate higher levels of enthusiasm, commitment, and a greater inclination to contribute to organizational success (Jannoyer et al., 2022; Ribeiro et al., 2021).			تُعد مشاركة الموظفين مؤشرًا مهمًا لأداء الموظفين. يُظهر الموظفون المتفاعلون مستويات أعلى من الحماس والالتزام وميلًا أكبر للمساهمة في النجاح المؤسسي.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Compensation:			**التعويض:**
It can be argued that compensation plays a vital role in employee performance. Adequate and fair compensation is linked to higher job satisfaction, motivation, and retention, all of which contribute to enhanced employee performance (Ratnasari et al., 2019; Syahruna et al., 2017).			يمكن القول بأن التعويضات تلعب دورًا حيويًا في أداء الموظفين. ترتبط التعويضات الكافية والعادلة بزيادة الرضا الوظيفي والتحفيز والاحتفاظ بالموظفين، وكلها تساهم في تعزيز أداء الموظف.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Organizational Commitment:			**الالتزام التنظيمي:**
Organizational commitment is defined as the psychological attachment an employee has to their organization. Higher levels of organizational commitment are associated with increased employee motivation and performance (Marlina et al., 2022; Likdanawati et al., 2022).			يُعرف الالتزام التنظيمي بأنه الارتباط النفسي للموظف بمنظمته. يترتبط المستويات الأعلى من الالتزام التنظيمي بزيادة تحفيز الموظفين وأدائهم.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمة للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Remuneration:			**التعويض:**
It can be argued that remuneration is a significant factor influencing employee performance. It is evident that remuneration, which encompasses not only salary but also other monetary benefits, plays a pivotal role in motivating employees. Fair and competitive remuneration can result in enhanced job satisfaction and productivity, as it reflects the organization's recognition of the employee's value (Ghiasvie et al., 2023).			يمكن القول بأن المكافأة عامل مهم يؤثر على أداء الموظفين. ومن الواضح أن المكافأة، التي لا تشمل الراتب فحسب، بل تشمل أيضاً المزايا النقدية الأخرى، تلعب دورًا محوريًا في تحفيز الموظفين. يمكن أن تؤدي المكافأة العادلة والتنافسية إلى تعزيز الرضا الوظيفي والإنتاجية، لأنها تعكس اعتراف المؤسسة بقيمة الموظف.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Working Environment:			**بيئة العمل:**
The working environment is of significant consequence with regard to employee performance. A work environment that is conducive to productivity and satisfaction, and which is safe, comfortable, and stimulating, has a significant impact on employee performance. Factors such as ergonomic office design and a positive organizational culture have been demonstrated to enhance the overall work experience, thereby leading to improved performance outcomes (Ghiasvie et al., 2023).			تتسم بيئة العمل بأهمية كبيرة فيما يتعلق بأداء الموظفين. فبيئة العمل المواتية للإنتاجية والراحة، والتي تتسم بالأمان والراحة والتحفيز، لها تأثير كبير على أداء الموظفين. وقد ثبت أن عوامل مثل التصميم المريح للمكاتب والثقافة التنظيمية الإيجابية تعزز تجربة العمل بشكل عام، مما يؤدي إلى تحسين نتائج الأداء.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Supervisory Assistance:			**المساعدة الإشرافية:**
It is believed to play a vital role in improving the performance of employees. The development of an employee largely depends on adequate support and guidance delivered by his or her supervisor, regular feedback, clear communication, and the provision of necessary resources. Positive relations with supervisors can make it easier to establish a supporting work environment, which, in turn, can enhance the engagement and performance of employees (Ghiasvie et al., 2023).			يُعتقد أنها تلعب دورًا حيويًا في تحسين أداء الموظفين. ويعتمد تطور الموظف إلى حد كبير على تقديم الدعم والتوجيه المناسبين من قبل المشرفين، التغذية الراجعة المنتظمة، والتواصل الواضح، وتوفير الموارد اللازمة. يمكن للعلاقات الإيجابية مع المشرفين أن تسهل إقامة بيئة عمل داعمة، والتي بدورها يمكن أن تعزز مشاركة الموظفين وأدائهم.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمة للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Physical Work Environment:			**البيئة المادية للعمل:**
The physical work environment, encompassing factors such as office layout, equipment quality, and workplace safety, has been demonstrated to exert a considerable influence on employee well-being and performance. A well-designed and safe work environment can mitigate fatigue and health risks, while simultaneously enhancing efficiency and job satisfaction (Nitzler, 2007).			يقصد بها البيئة المادية للعمل، التي تشمل عوامل مثل تخطيط المكاتب وجودة المعدات وسلامة مكان العمل، تؤثر تأثيرًا كبيرًا على رفاهية الموظفين وأدائهم. يمكن لبيئة العمل المصممة بشكل جيد وآمن أن تخفف من الإرهاق والمخاطر الصحية، مع تعزيز الكفاءة والرضا الوظيفي في الوقت نفسه.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Well-being and Mental Health:			**رفاهية الموظفين والصحة النفسية:**
The impact of employee well-being and mental health on job performance is increasingly being recognized. If left unaddressed, mental health issues can result in reduced productivity, absenteeism, and lower job satisfaction (Wright & Cropanzano, 2000).			يتزايد الاعتراف بتأثير رفاهية الموظفين وصحتهم العقلية على الأداء الوظيفي. إذا تُركت مشاكل الصحة العقلية دون معالجة، يمكن أن تؤدي مشاكل الصحة العقلية إلى انخفاض الإنتاجية والغياب عن العمل وانخفاض الرضا الوظيفي.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Team Dynamics and Peer Relationships:			**ديناميكيات الفريق وعلاقات الزملاء:**
The dynamics of teams and the relationships between colleagues within the workplace are of significant importance. The presence of positive team dynamics and supportive peer relationships has been demonstrated to enhance collaboration, morale, and motivation, thereby leading to improved performance (Tjeerald, 1984).			تعتبر ديناميكيات الفريق والعلاقات بين الزملاء في مكان العمل ذات أهمية كبيرة. وقد ثبت أن وجود ديناميكيات الفريق الإيجابية والعلاقات الداعمة بين الزملاء يعزز التعاون والروح المعنوية والتحفيز، مما يؤدي إلى تحسين الأداء.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Organizational Structure and Clarity:			**الهيكل التنظيمي والوضوح:**
The structure and clarity of an organization also have an impact on the performance of its employees. A well-structured organization with clearly delineated roles and responsibilities enables employees to comprehend their tasks and the manner in which they contribute to the organization's objectives, thereby enhancing efficiency and effectiveness (Hall et al., 2002).			يؤثر هيكل المنظمة وتنظيمها أيضاً على أداء موظفيها. فالمنظمة ذات الهيكل التنظيمي الجيد ذات الأدوار والمسؤوليات المحددة بوضوح تمكن الموظفين من فهم مهامهم والطريقة التي يساهمون بها في تحقيق أهداف المنظمة، وبالتالي تعزيز الكفاءة والفعالية.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Mentoring and Coaching:			**الإرشاد والتوجيه:**
These mentoring and coaching programs affect the development and performance of the employees. It helps them by giving proper guidance, advice, and support related to skill development, career growth, and work-related challenges, amongst others (Allen et al., 2004).			توفر برامج الإرشاد هذه على تطوير وأداء الموظفين فهي تساعدهم من خلال تقديم التوجيه والنصح والدعم المناسبين فيما يتعلق بتطوير المهارات والنمو الوظيفي والتحديات المتعلقة بالعمل وغيرها.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Workload and Job Design:			**عبء العمل وتصميم الوظيفة:**
The nature of the job and the workload given to an employee can significantly influence his performance. A well-designed job, for that matter which is commensurate to the skills and interests of the employee and matched with a workable level of load, could result in increased job satisfaction and better performance outputs (Parker et al., 2001).			يمكن أن يكون لطبيعة الوظيفة وعبء العمل المحدد إلى الموظف تأثير كبير على أدائه. فالوظيفة المصممة تصميماً جيداً، والتي تتناسب مع مهارات الموظف واهتماماته وتتناسب مع مستوى عبء العمل الذي يمكن تحقيقه، يمكن أن تؤدي إلى زيادة الرضا الوظيفي وتحسين مخرجات الأداء.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Resilience:			**مرونة الموظف:**
This is the ability of employees to bounce back from setbacks, adapt to changing circumstances, and maintain their mental well-being when facing difficulties. Resilient employees can sustain performance levels while experiencing stress or uncertainty and thus contribute to organizational robustness (Robertson et al., 2015).			وهي قدرة الموظفين على التعافي من الانتكاسات، والتكيف مع الظروف المتغيرة، والحفاظ على سلامتهم النفسية عند مواجهة الصعوبات. يمكن للموظفين المرنين الحفاظ على مستويات الأداء أثناء التعرض للضغوط أو عدم اليقين وبالتالي المساهمة في المتانة التنظيمية
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Innovation and Creativity:			**الابتكار والإبداع:**
The capacity for innovative and creative problem-solving is of greater importance in the contemporary workplace than ever before. The ability of employees to become creative thinkers and to bring solutions and innovations is of great benefit to an organization in maintaining its flexibility and competitiveness in the current economic climate (Anderson et al., 2014).			تكتسب القدرة على حل المشاكل بطريقة مبتكرة وإبداعية أهمية أكبر في مكان العمل المعاصر أكثر من أي وقت مضى. كما أن قدرة الموظفين على التفكير الإبداعي وتقديم الحلول والابتكارات ذات فائدة كبيرة للمؤسسة في الحفاظ على مرونتها وقدرتها التنافسية في المناخ الاقتصادي الحالي.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Change Management:			**إدارة التغيير:**
Properly handling organizational change, be it strategic, technological, or structural, has enabled an employer to adapt quickly. Proper change management reduces resistance to change, increases employee engagement, and thereby positively influences employee performance in the organization (Lasrado et al., 2022).			إن التعامل السليم مع التغيير التنظيمي، سواء كان تغييرًا استراتيجيًا أو تكنولوجيًا أو هيكليًا، يمكن الموظف من التكيف بسرعة. فالإدارة السليمة للتغيير تقلل من مقاومة التغيير، وتزيد من مشاركة الموظفين. وبالتالي تؤثر بشكل إيجابي على أداء الموظفين في المؤسسة
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Diversity and Inclusion in the Workplace:			**التنوع والشمول في مكان العمل:**
A diverse and inclusive work environment gives the employees a sense of belonging. Such environments encourage the expression of different views and ideas, thereby increasing creativity, innovation, and problem-solving from the bottom up. Employees were observed to be more satisfied and engaged in their work, reflecting their performance (Roberson, 2006).			تسمح بيئة العمل المتنوعة والشاملة للموظفين شعورًا بالانتماء. وتشجع مثل هذه البيئات على التعبير عن وجهات النظر والأفكار المختلفة، مما يزيد من الإبداع والابتكار وحل المشكلات من الأسفل إلى الأعلى. وقد لوحظ أن الموظفين أكثر رضا وانخراطًا في عملهم، مما ينعكس على أدائهم.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Recognition and Reward Systems:			**نظام الاعتراف والمكافآت للموظفين:**
These systems encourage employees and spur their performance. Whenever employees realize that their efforts are recognized and rewarded, their morale and commitment increase, therefore raising job satisfaction and productivity (Bean & Dagger, 2008).			تشجع هذه الأنظمة الموظفين وتحفزهم على الأداء. فكلما أدرك الموظفون أن جهودهم تحظى بالتقدير والمكافآت، ارتفاع معنوياتهم والتزامهم. وبالتالي يرتفع مستوى الرضا الوظيفي والإنتاجية
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Work Autonomy and Flexibility:			**الاستقلالية والمرونة في العمل:**
Autonomy at work and flexibility regarding time and place for work gives employees satisfaction with the job, reduce stress, and create a balance between work and life. Such practices enhance employee engagement and performance due to higher levels of trust from employers in the organization (Baltes et al., 1999).			إن الاستقلالية في العمل والمرونة بشأن وقت ومكان العمل تمنح الموظفين الرضا عن الوظيفة، وتقلل من التوتر، وتحقق التوازن بين العمل والحياة. تعزز مثل هذه الممارسات من مشاركة الموظفين وأدائهم بسبب ارتفاع مستويات ثقة الموظفين في المؤسسة.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Sustainability and Ethical Practices:			**الاستدامة والممارسات الأخلاقية:**
Employees nowadays look for their loyalty, job satisfaction, and engagement based on organizational commitments regarding sustainability and ethical practices. Hence, Organizational Sustainability Practices and Ethical Standards hold critical importance (Aguinis & Glavas, 2019).			يبحث الموظفون في الوقت الحاضر عن ولائهم ورضاهم الوظيفي ومشاركتهم بناءً على الالتزامات التنظيمية فيما يتعلق بالاستدامة والممارسات الأخلاقية. وبالتالي، تكتسب ممارسات الاستدامة التنظيمية والمعايير الأخلاقية أهمية بالغة.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Mental Health and Wellness Programs:			**برامج الصحة النفسية والعافية:**
The explicit reference to mental health support and wellness programs indicates that the organization is committed to a more holistic approach to employee health and well-being than has previously been the case. The support mechanism is no longer limited to the traditional scope of assistance but encompasses the prevention of mental illness and the implementation of wellness initiatives (Montgomery et al., 2019).			تمثل الإشارة الصريحة إلى برامج دعم الصحة النفسية والعافية إلى أن المؤسسة ملتزمة بتبني نهج أكثر شمولية تجاه صحة الموظفين وعافيتهم مما كان عليه الحال في السابق. لم تعد آلية الدعم تقتصر على النطاق التقليدي للمساعدة، بل أصبحت تشمل الوقاية من الأمراض النفسية وتنفيذ مبادرات العافية.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Inclusion Beyond Diversity:			**الشمولية إلى جانب التنوع:**
Although diversity and inclusion are often considered to be one and the same, there is a particular emphasis on inclusive practices. It is important to create an environment where all employees feel valued and included, not just because of the diversity of the workforce (Shore et al., 2011).			على الرغم من أن التنوع والشمول غالبًا ما يعتبران شيئًا واحدًا، إلا أن هناك تركيزًا خاصًا على الممارسات الشاملة. من المهم خلق بيئة يشعر فيها جميع الموظفين بالتقدير والشمول، وليس فقط بسبب تنوع القوى العاملة.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Agility and Innovation Culture:			**ثقافة المرونة والابتكار:**
Organizational Agility and Innovation Culture can be added to capture the dynamic aspects of organizational environments. These factors suggest that culture enables quick adaptability and continuous innovation in organizations (Dyer & Shafer, 2003).			يمكن إضافة الرشاقة التنظيمية وثقافة الابتكار لالتقاط الجوانب الديناميكية للبيئات التنظيمية. وتشير هذه العوامل إلى أن الثقافة تتيح القدرة على التكيف السريع والابتكار المستمر في المؤسسات.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Digital Literacy and Skills:			**المعرفة والمهارات الرقمية:**
In the modern digital era, the foundation of success is the ability of an individual to utilize digital tools and platforms effectively. Those who demonstrate proficiency in digital literacy are more effective in the execution of their duties, demonstrate greater agility in adapting to novel technologies, and consistently maintain optimal productivity (Van Laar et al., 2017).			في العصر الرقمي الحديث، يتمثل أساس النجاح في قدرة الفرد على استخدام الأدوات والمنصات الرقمية بفعالية. فإنهم الذين يظهرون الكفاءة في محو الأمية الرقمية يكونون أكثر فعالية في تنفيذ واجباتهم، وتظهرون مرونة أكبر في التكيف مع التقنيات الجديدة، ويحافظون باستمرار على الإنتاجية المثلى.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Organizational Transparency:			**الشفافية التنظيمية:**
The implementation of high levels of transparency in managerial practice, decision-making, and communication practices has been demonstrated to enhance levels of trust among employers, which, in turn, has been shown to positively impact their morale and performance. Transparent communication should be conducted in a manner that clearly delineates the organizational goals and objectives, while also addressing any concerns related to fairness (Schnackenberg & Tomlinson, 2016).			قد تبين أن تطبيق مستويات عالية من الشفافية في الممارسة الإدارية واتخاذ القرارات وممارسات التواصل يعزز مستويات الثقة بين الموظفين، والتي بدورها تؤثر إيجابًا على معنوياتهم وأدائهم. يجب أن يتم التواصل الشفاف بطريقة تحدد بوضوح الأهداف والغايات التنظيمية، مع معالجة أي مخاوف تتعلق بالعدالة
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Psychological Safety:			**السلامة النفسية**
A work environment that encourages employees to express their opinions, take calculated risks without fear of negative consequences, and be themselves is conducive to high levels of engagement, innovation, and performance (Edmondson, 1999).			إن بيئة العمل التي تشجع الموظفين على التعبير عن آرائهم وتحمل المخاطر المحسوبة دون خوف من العواقب السلبية، وأن يكونوا على طبيعتهم تؤدي إلى مستويات عالية من المشاركة والابتكار والأداء.
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Integration of Technology and Work Practices:			**دمج التكنولوجيا وممارسات العمل:**
The impact of today's digital transformation, increased relevance of Digital Fluency, and Adaptation to Remote Work are some factors that depict the practical usage of digital tools and working through new modes such as telecommuting and virtual collaboration (Allen et al., 2015).			إن تأثير التحول الرقمي اليوم، والأهمية المتزايدة للطلاقة الرقمية، والتكيف مع العمل من بعد في بعض العوامل التي توضح الاستخدام العملي للأدوات الرقمية والعمل من خلال أنماط جديدة مثل العمل من بعد والتعاون الافتراضي
When indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Technological Competence and Support:			**الكفاءة والدعم التكنولوجي:**
Technological training and support are provided on an ongoing basis, enabling employees to remain proficient in new technologies and thereby facilitate optimal performance. In their 2017 study, Van Laar and colleagues emphasised the significance of digital skills in enhancing employee productivity.			يتم توفير التدريب والدعم التكنولوجي على أساس مستمر، مما يمكن الموظفين من الحفاظ على كفاءتهم في التقنيات الجديدة وبالتالي تسهيل الأداء الأمثل. في دراسيم لعام 2017، أكد فان لار وزملاؤه على أهمية المهارات الرقمية في تعزيز إنتاجية الموظفين
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Environmental Sustainability Initiatives:			**مبادرات الاستدامة البيئية:**
Employees become more purposeful in sustaining the environment and identify more with organisational values, which translates to increased engagement and performance. Agyemi and Glenas (2019) also noted that sustainability practices correlated with better employee motivation and performance.			يمكن أن تؤدي مشاركة الموظفين في جهود الاستدامة إلى منظماتهم إلى زيادة انسجامهم والتوافق مع قيم المنظمة، مما يؤدي إلى زيادة المشاركة والأداء. وقد أشار Agyemi و Glenas (2019) أن ممارسات الاستدامة مرتبطة بزيادة تحفيز الموظفين وأدائهم
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Crisis Management Training:			**تدريب إدارة الأزمات:**
The preparation of employees who are able to manage crises ensures the maintenance of performance under pressure, thus reducing stress and enhancing resilience levels during the crisis period. A study conducted by Caswell and Schaubroeck (2008) demonstrated that crisis management preparedness enhances employees' coping mechanisms and performance under pressure.			يضمن إعداد الموظفين القادرين على إدارة الأزمات الحفاظ على الأداء تحت الضغط، وبالتالي تقليل التوتر وتعزيز مستويات المرونة خلال فترة الأزمات. أظهرت دراسة أجراها كاسويل وشوبروك (2008) أن الاستعداد لإدارة الأزمات يعزز آليات التأقلم والأداء تحت الضغط لدى الموظفين
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Personal Development Opportunities:			**فرص التنمية الشخصية:**
It is through these opportunities that an individual grows and develops, and that translates to satisfaction with the job performance and motivation to work, hence enhancement of the worker's performance. Londico and Smither (1999) found positive effects of opportunities to engage in lifelong learning on job performance and career development.			من خلال هذه الفرص ينمو الفرد ويتطور، وهذا يُترجم إلى الرضا عن الأداء الوظيفي والتحفيز على العمل. وبالتالي تعزيز أداء العامل. وجد كل من لندن وسميثر (1999) أن إتاحة الفرص للانخراط في التعلم مدى الحياة على الأداء الوظيفي والتطور الوظيفي
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Remote Work Capability:			**القدرة على العمل من بُعد:**
The remote working facility brings work-life balance by offering flexibility and reducing the time spent commuting, which in turn enhances performance. A synthesis of several pieces of research indicates that remote work increases job satisfaction and performance. This is because remote work offers workers flexibility in every aspect of their work life (Bloom et al., 2015).			يحقق العمل من بُعد التوازن بين العمل والحياة الشخصية من خلال توفير المرونة وتقليل الوقت المستغرق في التنقل، مما يعزز بدوره الأداء. يشير تجميع لعدة أبحاث إلى أن العمل من بُعد يزيد من الرضا الوظيفي والأداء. وذلك لأن العمل عن بُعد يوفر للعاملين المرونة في كل جانب من جوانب حياتهم العملية
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Workplace Well-being Programs:			**برامج رفاهية مكان العمل:**
Worksite health promotion programs with a holistic approach to physical fitness, nutritional status, and stress reduction may reduce absenteeism and improve the general well-being of an employee. It was stated by Gomzel et al. (2014) that there was a direct relationship between well-being programs, decreasing healthcare costs, and increased productivity.			قد تقلل برامج تعزيز الصحة في موقع العمل مع اتباع نهج شامل للياقة البدنية والحالة الغذائية والحد من الإجهاد من الغياب عن العمل وتحسين الرفاهية العامة للموظف. وقد ذكر غوميل وآخرون (2014) أن هناك علاقة مباشرة بين برامج الرفاهية وتقليص تكاليف الرعاية الصحية وزيادة الإنتاجية
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Diversity in Leadership:			**التنوع في القيادة:**
Having diversity in leadership entices employees from different backgrounds and, therefore, gives them a sense of belonging, consequently resulting in high commitment. This propels their performance. The findings of McKinsey & Company (2020) reveal that companies with diverse leadership teams outperform others.			إن وجود التنوع في القيادة يغري الموظفين من خلفيات مختلفة، وبالتالي يمنحهم شعورًا بالانتماء، مما يؤدي بالتالي إلى التزام عالٍ. وهذا يدفع أدائهم. تكشف النتائج التي توصلت إليها شركة ماكنزي آند كومباني (2020) أن الشركات التي لديها فرق قيادية متنوعة تتفوق على غيرها
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Employee Voice and Participation:			**صوت الموظف والمشاركة:**
The incorporation of employee input into decision-making processes fosters a sense of ownership and commitment, which in turn leads to enhanced performance. The study by Wilkinson et al. (2018) found that employee voices and participation during decision-making processes stimulate innovations and continuous improvements in organisations, which positively impact motivation and, therefore, performance.			إن إشراك مدخلات الموظفين في عمليات صنع القرار يعزز الشعور بالملكية والالتزام، وهو ما يؤدي بدوره إلى تحسين الأداء. وجدت الدراسة التي أجراها ويلكنسون وآخرون (2018) أن آراء الموظفين ومشاركتهم في عمليات صنع القرار تحفز الابتكارات والتحسينات المستمرة في المؤسسات، مما يؤثر إيجابًا على التحفيز. وبالتالي على الأداء
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Factors Affecting Employee Performance	ملائمتها للقطاع العام في البحرين		العوامل المؤثرة على أداء الموظفين
	لا	نعم	
Employee Social Networks:			**شبكات الموظفين الاجتماعية:**
Social networks in the organisation can assist in shared experiences by employees within their location-based networks and gain support. For instance, Cross and Cummings (2004) found that social networks within organisations enhance knowledge flow and performance.			يمكن للشبكات الاجتماعية في المنظمة أن تساعد في تبادل الخبرات بين الموظفين داخل شبكاتهم القائمة على المواقع والدعم الفعلي. على سبيل المثال، وجد كروس وكامينغز (2004) أن الشبكات الاجتماعية داخل المنظمات تعزز تدفق المعرفة والأداء
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:
Feedback Culture:			**ثقافة التغذية الراجعة:**
Establishing the norm of giving regular, constructive feedback will help employees continually improve performance and address problems as they arise. Kluger and DeNisi (1996) proved that feedback interventions result in significant increases in employee performance because they provide clear guidelines regarding the areas one might develop.			سيساعد إرساء قاعدة تقديم تغذية راجعة منتظمة وبناءة الموظفين على تحسين الأداء باستمرار ومعالجة المشاكل عند ظهورها. وقد أثبت كلوجر وبينيسي (1996) أن التدخلات الخاصة بالتغذية الراجعة تؤدي إلى زيادة كبيرة في أداء الموظف لأنها توفر إرشادات واضحة فيما يتعلق بالمجالات التي يمكن للمرء تطويرها
If/when indicating "No", please provide a justification:			عند الإشارة بـ (لا)، يرجى ذكر المبررات:

Additional factors that may affect the performance of employees in Bahrain's public sector	عوامل إضافية قد تؤثر على أداء الموظفين في القطاع العام في البحرين
The name of the influencing factor is:	**اسم العامل المؤثر:**
Please provide your expert opinion on this factor:	يرجى تقديم رأيك الخبير في هذا العامل:
Please provide a rationale for the addition, outlining how this factor affects the performance of public sector employees:	يرجى تقديم السبب المنطقي للإضافة، مع توضيح كيفية تأثير هذا العامل على أداء موظفي القطاع العام:
The name of the influencing factor is:	**اسم العامل المؤثر:**
Please provide your expert opinion on this factor:	يرجى تقديم رأيك الخبير في هذا العامل:
Please provide a rationale for the addition, outlining how this factor affects the performance of public sector employees:	يرجى تقديم السبب المنطقي للإضافة، مع توضيح كيفية تأثير هذا العامل على أداء موظفي القطاع العام:
The name of the influencing factor is:	**اسم العامل المؤثر:**
Please provide your expert opinion on this factor:	يرجى تقديم رأيك الخبير في هذا العامل:
Please provide a rationale for the addition, outlining how this factor affects the performance of public sector employees:	يرجى تقديم السبب المنطقي للإضافة، مع توضيح كيفية تأثير هذا العامل على أداء موظفي القطاع العام:
The name of the influencing factor is:	**اسم العامل المؤثر:**
Please provide your expert opinion on this factor:	يرجى تقديم رأيك الخبير في هذا العامل:
Please provide a rationale for the addition, outlining how this factor affects the performance of public sector employees:	يرجى تقديم السبب المنطقي للإضافة، مع توضيح كيفية تأثير هذا العامل على أداء موظفي القطاع العام:
The name of the influencing factor is:	**اسم العامل المؤثر:**
Please provide your expert opinion on this factor:	يرجى تقديم رأيك الخبير في هذا العامل:
Please provide a rationale for the addition, outlining how this factor affects the performance of public sector employees:	يرجى تقديم السبب المنطقي للإضافة، مع توضيح كيفية تأثير هذا العامل على أداء موظفي القطاع العام:

Appendix (B) Participant Demographic Tables

A: Table of Expert Interviews

Participant Code	Professional Title/Role	Affiliated Ministry/Entity	Years of Experience
E01	Senior HR Specialist	Commerce	23
E02	HR Manager	Health	21
E03	Former Deputy Minister	Education and Training	25+
E04	Policy Advisor	Labor, social affairs	20
E05	Senior Policy Analyst	Public Service	21
E06	Training Coordinator	Labor, social affairs	18
E07	Deputy Director	Agriculture and Animal Wealth	25+
E08	HR Consultant	Economics and Finance	19
E09	Program Manager	Justice and Legal Affairs	22
E10	Assistant Deputy Minister	Sports and Youth	20
E11	HR Team Leader	Environment and Sustainable Development	21
E12	Human Capital Officer	Energy and Water Resources	25+
E13	Assistant Director	Foreign Affairs	20
E14	Senior Government Official	Municipalities	17
E15	Talent Acquisition Manager	Housing and Urban Planning	21
E16	Workforce Planning Advisor	Media	25+
E17	HR Systems Analyst	Civil Service Council	19
E18	Project Leader	Information and Statistics	21
E19	Strategic Planning Manager	Culture and Tourism	22
E20	Management Expert	Public Service	17
E21	Senior Specialist	Transportation	19
E22	HR Expert	Executive councils	23

B: Table of Focus Group Discussions Participation

Participant Code	Current Position	Affiliated Ministry/Entity	Experience Range
FGD01	Administrative Supervisor	Health	16–20
FGD02	Policy Analyst	Education and Training	11–15
FGD03	HR Officer	Municipalities	11–15
FGD04	Finance Officer	Housing and Urban Planning	6–10
FGD05	Technical Specialist	Technology	11–15
FGD06	Academic Expert	Education and Training	11–15
FGD07	Quality Assurance Analyst	Executive councils	16–20
FGD08	Regulatory Inspector	Media	11–15
FGD09	Research Coordinator	Transportation	16–20
FGD10	Social Services Specialist	Energy and Water Resources	11–15
FGD11	Economic Planner	Economy and Commerce	11–15
FGD12	Budget Analyst	Agriculture and Animal Wealth	11–15
FGD13	Compliance Officer	Shora, Parliament	16–20
FGD14	IT Manager	Environment and Sustainable Development	11–15
FGD15	Government Liaison Officer	Culture and Tourism	11–15
FGD16	Audit Officer	Health	16–20
FGD17	Communications Officer	Justice and Legal Affairs	11–15
FGD18	Logistics Coordinator	Economics and Finance	11–15
FGD19	Environmental Engineer	Information and Statistics	16–20
FGD20	Project Manager	Foreign Affairs	11–15
FGD21	Training Officer	Labor, social affairs	16–20
FGD22	Planning Officer	Executive councils	11–15
FGD23	Administrative Officer	Energy and Water Resources	16–20

Appendix (C) Thematic Analysis Outputs Using Nvivo

Thematic Analysis of Expert Interview Findings:

NVivo Coding Frequency for the 54 Initial Factors (Round 1)

No.	Factor	Frequency	Percentage (%)
1	Public Service Motivation (PSM)	80	2.4
2	Job Satisfaction	90	2.8
3	Organizational Commitment	85	2.6
4	Proactive Behavior	70	2.1
5	Organizational Citizenship Behaviors (OCBs)	65	2.0
6	Employee Autonomy	75	2.3
7	Emotional Intelligence (EI)	80	2.4
8	Communication Skills	75	2.3
9	Knowledge-Sharing Ability	85	2.6
10	Cognitive Abilities	70	2.1
11	Competence	95	2.9
12	Adaptability	65	2.0
13	Employee Resilience	60	1.8
14	Digital Literacy and Skills	55	1.7
15	Team Dynamics and Peer Relationships	60	1.8
16	Employee Social Networks	50	1.5
17	Leadership Style	100	3.1
18	Supervisory Assistance	80	2.4
19	Diversity in Leadership	45	1.4
20	Change Management	70	2.1
21	Organizational Culture	105	3.2
22	Organizational Transparency	50	1.5
23	Work Climate	85	2.6
24	Working Environment	60	1.8
25	Physical Work Environment	55	1.7
26	Organizational Structure and Clarity	65	2.0
27	Job Design and Workload	70	2.1
28	Technological Advancement	50	1.5
29	Technological Competence and Support	45	1.4
30	Integration of Technology and Work Practices	40	1.2
31	High-Performance Work Systems (HPWS)	55	1.7

32	Innovation and Creativity	60	1.8
33	Agility and Innovation Culture	45	1.4
34	Employee Well-being and Mental Health	70	2.1
35	Mental Health and Wellness Programs	40	1.2
36	Workplace Well-being Programs	35	1.1
37	Work-Life Balance (WLB)	80	2.4
38	Psychological Safety	60	1.8
39	Compensation	50	1.5
40	Remuneration	45	1.4
41	Employee Recognition and Reward Systems	60	1.8
42	Employee Engagement	90	2.8
43	Employee Voice and Participation	55	1.7
44	Work Autonomy and Flexibility	50	1.5
45	Remote Work Capability	40	1.2
46	Training and Development Opportunities	55	1.7
47	Crisis Management Training	35	1.1
48	Personal Development Opportunities	50	1.5
49	Mentoring and Coaching	40	1.2
50	Feedback Culture	45	1.4
51	Workplace Diversity and Inclusion	40	1.2
52	Inclusion Beyond Diversity	35	1.1
53	Sustainability and Ethical Practices	30	0.9
54	Environmental Sustainability Initiatives	25	0.8
Total		**3270**	**100**

Note: This table summarizes the coding frequency and percentage representation of 54 initially identified factors based on expert interviews and qualitative analysis. Key factors with high coding frequencies include Organizational Culture, Leadership Style, Competence, Employee Engagement, and Job Satisfaction, highlighting their perceived importance among experts during the initial phase of the analysis. Percentages are calculated as (Frequency/3270) × 100.

NVivo Coding Frequency for the 46 Refined Factors (Round 2)

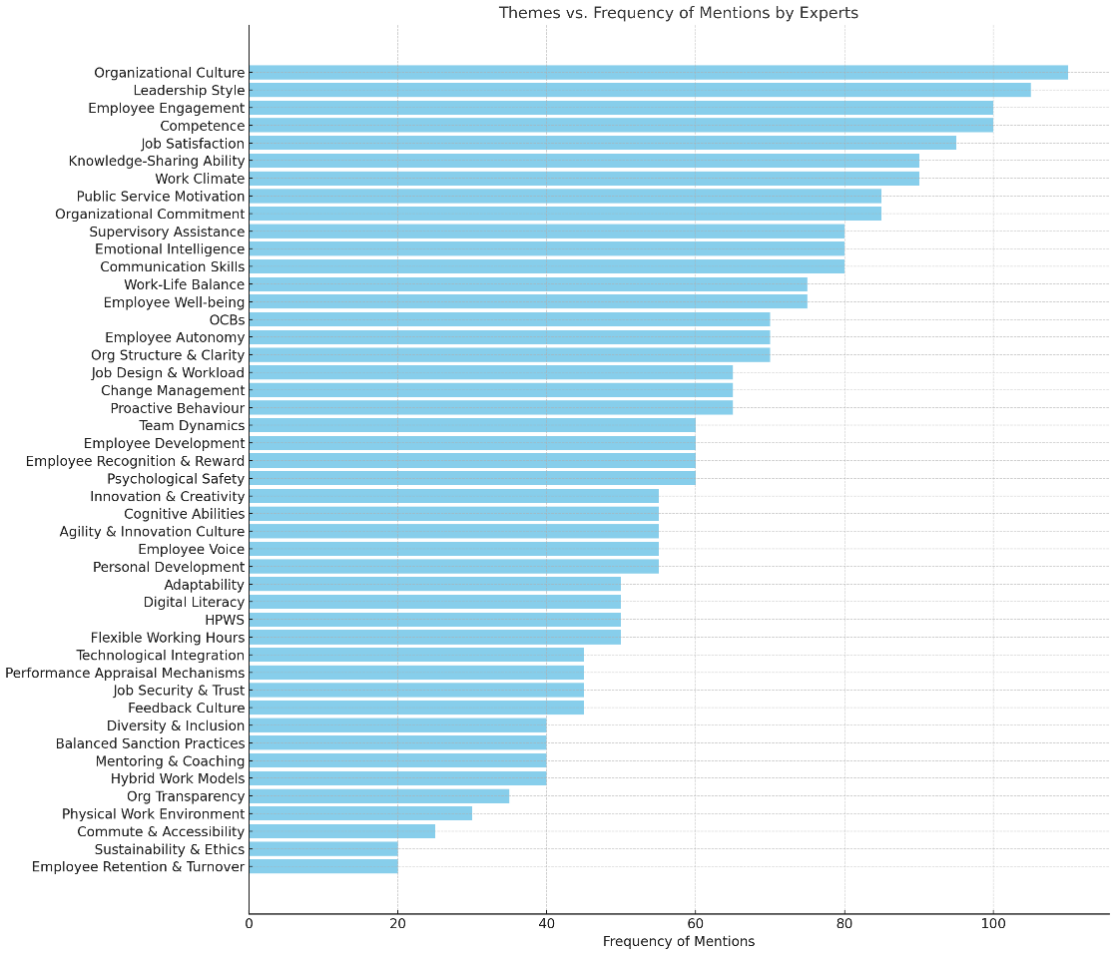
No.	Factor	Frequency	Percentage (%)
1	Public Service Motivation (PSM)	85	3.0
2	Job Satisfaction	95	3.3
3	Work-Life Balance	75	2.6
4	Employee Recognition and Reward Systems	60	2.1
5	Flexible Working Hours (New Factor)	50	1.8

6	Communication Skills	80	2.8
7	Organizational Citizenship Behaviors (OCBs)	70	2.5
8	Proactive Behavior	65	2.3
9	Employee Voice and Participation	55	1.9
10	Feedback Culture	45	1.6
11	Knowledge-Sharing Ability	90	3.2
12	Competence	100	3.5
13	Employee Development	60	2.1
14	Digital Literacy and Skills	50	1.8
15	Mentoring and Coaching	40	1.4
16	Personal Development Opportunities	55	1.9
17	Leadership Style	105	3.7
18	Supervisory Assistance	80	2.8
19	Change Management	65	2.3
20	Performance Appraisal Mechanisms (New Factor)	45	1.6
21	Balanced Sanction System Practices (New Factor)	40	1.4
22	Organizational Culture	110	3.9
23	Work Climate	90	3.2
24	Agility and Innovation Culture	55	1.9
25	Employee Engagement	100	3.5
26	Organizational Commitment	85	3.0
27	Team Dynamics and Peer Relationships	60	2.1
28	Organizational Structure and Clarity	70	2.5
29	High-Performance Work Systems (HPWS)	50	1.8
30	Technological Integration and Competence	45	1.6
31	Hybrid Work Models (New Factor)	40	1.4
32	Innovation and Creativity	55	1.9
33	Job Design and Workload	65	2.3
34	Emotional Intelligence (EI)	80	2.8
35	Psychological Safety	60	2.1
36	Employee Well-being and Mental Health	75	2.6
37	Employee Autonomy	70	2.5
38	Cognitive Abilities	55	1.9
39	Adaptability	50	1.8
40	Job Security and Trust (New Factor)	45	1.6
41	Diversity and Inclusion	40	1.4

42	Organizational Transparency	35	1.2
43	Physical Work Environment	30	1.1
44	Commute and Accessibility (New Factor)	25	0.9
45	Sustainability and Ethical Practices	20	0.7
46	Employee Retention and Turnover (New Factor)	20	0.7
Total		**2840**	**100**

Note: This table presents the coding frequency and percentage for the refined set of 46 factors after expert review and further qualitative analysis. New factors introduced in this round, such as Flexible Working Hours, Performance Appraisal Mechanisms, Balanced Sanction System Practices, Hybrid Work Models, Job Security and Trust, Commute and Accessibility, and Employee Retention and Turnover, reflect the evolution of expert discussions and the increased focus on contemporary organizational practices. The percentages are calculated as (Frequency/2840) × 100.

Frequency of Mentions of Key Themes by Experts



Note: This bar chart illustrates the frequency with which experts cited various organizational and management-related themes. The most frequently mentioned themes include Organizational Culture, Leadership Style, Employee Engagement, Competence, and Job Satisfaction. Less frequently cited themes include Employee Retention and Turnover, Sustainability and Ethics, and Commute and Accessibility.

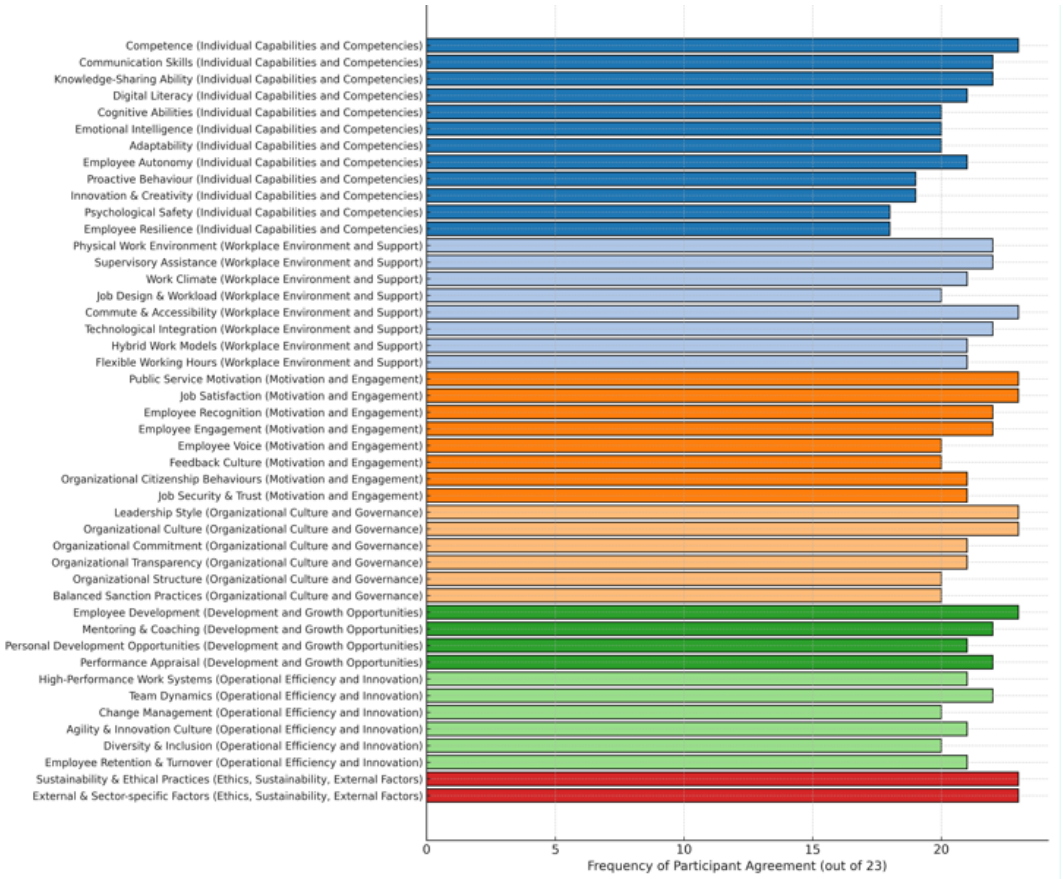
Thematic Analysis of Focus Group Discussions (FGDs)

Frequency Distribution of Factors within Thematic Categories from FGDs (N=23 Participants)

Thematic Category	Factors (with frequency ≥20/23 indicating high consensus)
Individual Capabilities and Competencies	Competence (23), Communication Skills (22), Knowledge-Sharing Ability (22), Digital Literacy (21), Cognitive Abilities (20), Emotional Intelligence (20), Adaptability (20), Employee Autonomy (21), Proactive Behavior (19), Innovation and Creativity (19), Psychological Safety (18), Employee Resilience (18)
Workplace Environment and Support	Physical Work Environment (22), Supervisory Assistance (22), Work Climate (21), Job Design and Workload (20), Commute and Accessibility (23), Technological Integration (22), Hybrid Work Models (21), Flexible Working Hours (21)
Motivation and Engagement	Public Service Motivation (23), Job Satisfaction (23), Employee Recognition (22), Employee Engagement (22), Employee Voice (20), Feedback Culture (20), Organizational Citizenship Behaviors (21), Job Security and Trust (21)
Organizational Culture and Governance	Leadership Style (23), Organizational Culture (23), Organizational Commitment (21), Organizational Transparency (21), Organizational Structure (20), Balanced Sanction System Practices (20)
Development and Growth Opportunities	Employee Development (23), Mentoring and Coaching (22), Personal Development Opportunities (21), Performance Appraisal Mechanisms (22)
Operational Efficiency and Innovation	High-Performance Work Systems (21), Team Dynamics (22), Change Management (20), Agility and Innovation Culture (21), Diversity and Inclusion (20), Employee Retention & Turnover (21)
Ethics, Sustainability and External Factors	Sustainability and Ethical Practices (23), Commute and Accessibility (23)

Note: Frequencies represent the number of participants (out of 23) who independently agreed on assigning each factor into the specified thematic category. Higher frequencies indicate stronger consensus among participants and greater thematic clarity, enhancing the empirical robustness of the qualitative findings.

Participant Agreement on Factor Categorization by Thematic Category



Note: This chart illustrates the number of participants (out of 23) who assigned each factor to the thematic category shown. It reflects the level of consensus and the empirical strength of categorization across the four focus groups.

Appendix (D) The Questionnaire

A. English version of the Survey

Thank you for taking the time to participate in this survey. Your contribution is of great value to our research, which is focused on enhancing employee performance management through the utilization of AI-enabled predictive and decision-making models. The principal objective of this study is to ascertain the various factors that influence employee performance in the Bahraini public sector, with a view to developing innovative solutions that enhance organizational outcomes.

The objective of this research is to examine the influence of individual capabilities, workplace environments, motivation, organizational culture and other factors on employee performance. The insights gained will inform the design of models to predict and enhance performance, thereby contributing to the creation of a more efficient and supportive work environment in the public sector.

Your responses will be treated in the strictest confidence and will be used solely for academic research purposes. It is guaranteed that no personally identifiable information will be shared or disclosed. The data collected will be anonymized and stored securely to ensure privacy.

The questionnaire is designed to take approximately 5-10 minutes to complete. Please answer each question honestly and to the best of your ability.

Should you have any queries or concerns pertaining to this survey or the research, you are invited to contact the researcher at alsobaey@hotmail.com.

Thank you again for your participation. Your contribution is greatly appreciated.

First: Demographic data and job-related information

1. **Gender:**
   - Male
   - Female

2. **Age group:**
   - 24 and younger
   - From 25-34
   - From 35-44
   - From 45-54
   - From 55-64
   - 65 years and above

3. **Educational level:**
   - High school diploma, diploma, or equivalent
   - Bachelor's degree
   - Master's degree
   - Doctorate degree

4. **Job title/position in your organization:**
   - Minister / Undersecretary / CEO
   - Assistant Undersecretary / Director General / Manager
   - Chief / Supervisor / Team Leader
   - Senior Specialist / Specialist
   - Administrative Technician

5. **Sector type:**

- Health
- Education and Training
- Municipalities
- Housing and Urban planning
- Technology
- Media
- Transportation
- Energy, Space and Water Resources
- Economy and Commerce
- Agriculture and Animal Wealth
- Environment and Sustainable Development
- Culture and Tourism
- Justice and Legal Affairs
- Economics and Finance
- Information and Statistics
- Foreign Affairs, International Relations and Diplomacy
- Labor, social affairs and the labor market
- Shora, Parliament and Executive councils

6. Years of experience in the public sector:

- Less than 5 years
- From 5 to 10 years
- From 11 to 15 years
- From 16 to 20 years
- More than 20 years

Secondly: Choose the appropriate answer from the given phrases, indicating each number as follows (5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree).

Category A: Individual Capabilities and Competencies

1. **Public Service Motivation (PSM)**
    - *"I am motivated by a desire to serve the public and contribute to the common good."*
2. **Knowledge-Sharing Ability**
    - *"I frequently share knowledge and expertise with my colleagues to improve team outcomes."*
3. **Emotional Intelligence (EI)**
    - *"I am able to recognize and manage my emotions effectively in challenging work situations."*
4. **Cognitive Abilities**
    - *"I excel at analyzing complex information and solving problems at work."*
5. **Adaptability**
    - *"I can easily adjust to changes in workplace tasks or policies."*
6. **Organizational Citizenship Behaviours (OCBs)**

- *"I take on additional tasks or responsibilities, within the scope of my role, to contribute to the organization's success."*

7. **Proactive Behaviour**
    - *"I take initiative to address issues or improve processes without being prompted."*
8. **Organizational Commitment**
    - *"I feel a strong sense of loyalty and commitment to my organization."*
9. **Competence**
    - *"I feel I possess the skills and knowledge needed to perform my job effectively."*
10. **Communication Skills**
    - *"I communicate clearly and effectively with colleagues, supervisors, and stakeholders."*
11. **Work-Life Balance**
    - *"I am able to maintain a healthy balance between my work and personal life."*
12. **Digital Literacy and Skills**
    - *"I am proficient in using digital tools and technologies required for my role."*

Category B: Workplace Environment and Support

1. **Physical Work Environment**
    - *"My workspace is comfortable and supports my ability to work efficiently."*
2. **Work Climate**
    - *"The overall work climate in my organization is positive and supportive."*
3. **Psychological Safety**
    - *"I feel safe expressing my ideas and concerns at work without fear of negative consequences."*
4. **Supervisory Assistance**
    - *"My supervisor provides the guidance and support I need to succeed in my role."*
5. **Team Dynamics and Peer Influence**
    - *"My team collaborates effectively and supports each other in achieving goals."*
6. **Change Management**
    - *"My organization manages change effectively, ensuring minimal disruption to work."*
7. **Employee Well-being and Mental Health**

- *"My organization provides resources and support to maintain my mental well-being."*

8. **Job Security and Trust**
    - *"I feel secure in my job and trust the organization to provide stability."*

Category C: Motivation and Engagement

1. **Job Satisfaction**
    - *"I am satisfied with my current role and responsibilities."*
2. **Employee Engagement**
    - *"I feel encouraged by my organization to care about its success and to contribute actively to achieving its goals."*
3. **Employee Autonomy**
    - *"I have the freedom to make decisions about how I perform my work."*
4. **Flexible Working Hours**
    - *"I am satisfied with the flexibility of my working hours."*
5. **Hybrid Work Models**
    - *"The hybrid work model supports my productivity and work-life balance."*
6. **Employee Retention and Turnover**
    - *"I see myself continuing to work for this organization in the long term."*
7. **Employee Recognition and Reward**
    - *"I feel recognized and rewarded for my contributions at work."*
8. **Employee Voice and Participation**

"I am given the chance to share my opinions on decisions that impact my work."

Category D: Organizational Culture and Governance

1. **Organizational Culture**
    - *"The culture in my organization fosters collaboration and innovation."*
2. **Leadership Style**
    - *"Leadership in my organization inspires and motivates employees."*
3. **Diversity and Inclusion**
    - *"My organization values diversity and fosters an inclusive work environment."*
4. **Organizational Transparency**
    - *"My organization clearly and openly explains important decisions and processes to employees."*

5. **Balanced Sanction System Practices**
    - *"Disciplinary actions in my organization are fair and applied equally"*
6. **Performance Appraisal Mechanisms**
    - *"The performance appraisal system in my organization is fair and constructive."*

Category E: Development and Growth Opportunities

1. **Employee Development**
    - *"My organization provides adequate training and development opportunities."*
2. **Personal Development Opportunities**
    - *"I have opportunities to develop skills that contribute to my personal growth."*
3. **Mentoring and Coaching**
    - *"I have access to mentoring or coaching programs that support my career growth."*
4. **Feedback Culture**
    - *"Constructive feedback is regularly provided to help me improve my performance."*

Category F: Operational Efficiency and Innovation

1. **High-Performance Work Systems (HPWS)**
    - *"My organization's work systems are designed to maximize efficiency and performance."*
2. **Agility and Innovation Culture**
    - *"My organization is agile and adapts well to changes and innovations."*
3. **Job Design and Workload**
    - *"My workload is well-managed, and tasks are aligned with my skills."*
4. **Technological Integration and Competence**
    - *"The technological tools provided by my organization enhance my productivity."*
5. **Innovation and Creativity**
    - *"My organization encourages innovation and creative problem-solving."*
6. **Organizational Structure and Clarity**
    - *"Roles and responsibilities within my organization are clearly defined."*

Category G: Ethics, Sustainability, and External Factors

1. **Sustainability and Ethical Practices**
    - *"My organization operates ethically and contributes to sustainability goals."*
2. **Commute and Accessibility**
    - *"My commute to work is convenient and does not affect my productivity negatively."*

Third: Employee Performance (Outputs)

1. **Overall Performance Rating** (Self-reported, for the last three years) (5=Far exceeds expectations, 4=Exceeds expectations, 3=Fully Meets Expectations, 2=Partially Meets Expectations, 1=Needs Improvement)
    - *"How would you rate your overall performance at work in the past year?"*
    - *"How would you rate your overall performance two years ago?"*
    - *"How would you rate your overall performance three years ago?"*
2. **Goal Achievement**

    (5 = Fully Achieved, 4 = Mostly Achieved, 3 = Moderately Achieved, 2 = Rarely Achieved, 1 = Not at All).
    - *"To what extent did you meet your work goals in the past year?"*
3. **Perceived Effectiveness**

    (5 = Highly Effective, 4 = Effective, 3 = Moderately Effective, 2 = Slightly Effective, 1 = Not Effective).
    - *"How effective do you believe you are in achieving organizational objectives?"*
4. **Behavioral Indicators of Performance** (Optional)

    (5 = Very Often, 4 = Often, 3 = Sometimes, 2 = Rarely, 1 = Never).
    - *"How often do you receive recognition or commendations for your work?"*
    - *"How often do you exceed the expectations set for your role?"*

Appendix (E) Classification Model Algorithms

Gradient Boost Classifier

Training Objective and Steps

Let $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$ be the training data. Assume the current ensemble model after $t-1$ iterations are F_{t-1}(x). We want to improve this model by adding a new weak learner $h_t(\mathbf{x})$. For a differentiable loss function $L\big(y_i, F(\mathbf{x}_i)\big)$, The algorithm proceeds as follows:

1. Initialize the Model

   Start with a constant model:

$$F_0(\boldsymbol{x}) = arg\ \min_{\gamma} \sum_{i=1}^{N} L(y_i, \gamma)$$

2. Compute Residuals (Negative Gradients)

   For each training point, compute the gradient of the loss function with respect to the current model's predictions:

$$r_{i,t} = -\left[\frac{\partial L\big(y_i, F(\boldsymbol{x}_i)\big)}{\partial F(\boldsymbol{x}_i)}\right]_{F=F_{t-1}}$$

   which effectively serves as the "target" for the next weak learner.

3. Fit a Weak Learner to Residuals

   Train a new decision tree $h_t(\mathbf{x})$ to predict $r_{i,t}$. The goal is to approximate how the model should adjust its predictions to reduce the current errors.

4. Update the Model

   Update the ensemble with a scaling factor v (learning rate):

$$F_t(\boldsymbol{x}) = F_{t-1}(\boldsymbol{x}) + vh_t(\boldsymbol{x})$$

5. Iterate

   Repeat the process for a fixed number of boosting rounds T or until the improvements become negligible.

   The final model after T round is:

$$F_T(\boldsymbol{x}) = F_0(\boldsymbol{x}) + \sum_{t=1}^{T} vh_t(\boldsymbol{x})$$

Hyperparameters and Tuning

1. Number of Estimators (Trees): The number of boosting rounds T is a critical parameter. Although more trees can improve their fitness, going too high risks overfitting. Early stopping or cross-validation helps find the sweet spot.
2. Learning Rate (v): A smaller learning rate slows training but can improve generalization, as each tree makes a smaller update. It often works best in conjunction with a larger number of estimators.
3. Max Depth: Deeper trees can capture more complex patterns but increase the risk of overfitting. Limiting tree depth is a common form of regularization.
4. Min Samples per Leaf / Min Child Weight: This controls the minimum number of samples required in a leaf node. Restricting leaf size prevents overly specific splits, thus improving generalization.

XGBoost Classifier

Training Process and Objective Function

Let $F_{t-1}(\mathbf{x})$ be the ensemble learned up to round $t-1$. XGBoost adds a new tree h_t in round t, aiming to minimize a regularized loss:

$$\mathcal{O}_t = \sum_{i=1}^{N} L\big(y_i, F_{t-1}(\boldsymbol{x}_i) + h_t(\boldsymbol{x}_i)\big) + \Omega(h_t)$$

Using a second-order approximation around $F_{t-1}(\mathbf{x}_i)$, the problem of finding the optimal h_t boils down to choosing the best split structure and leaf weights. For each leaf, XGBoost computes the optimal weight w_j via aggregated first- and second-order derivatives:

$$w_j^* = -\frac{\sum_{i\in \text{ leaf }_j} g_i}{\sum_{i\in \text{ leaf }_j} h_i + \lambda}$$

Where λ is a regularization hyperparameter. Summing the contribution from each leaf (plus a penalty term γ for each leaf) gives the final improvement in the objective, and the algorithm greedily selects the splits that produce the largest gain.

Random Forest Classifier

- Gini Impurity at a node t is often defined as

$$Gini(t) = \sum_{k=1}^{K} p_k(t)\big(1 - p_k(t)\big)$$

where $p_k(t)$ is the fraction of samples in node t that belong to class k. The goal is to minimize this impurity when making splits.

- Entropy can also be used, given by

$$Entropy(t) = -\sum_{k=1}^{K} p_k(t) log_2\,(p_k(t))$$

K-Nearest Neighbors (KNN) Classifier

Distance Metrics

A key component of KNN is the distance function $d(.,.)$. Common choices include:

- Euclidean distance:

$$d(\boldsymbol{x}_i, \boldsymbol{x}_j) = \sqrt{\sum_{m=1}^{d} \left(x_{i,m} - x_{j,m}\right)^2}$$

- Manhattan distance:

$$d(\boldsymbol{x}_i, \boldsymbol{x}_j) = \sum_{m=1}^{d} \left|x_{i,m} - x_{j,m}\right|$$

- Minkowski distance (generalization):

$$d(\boldsymbol{x}_i, \boldsymbol{x}_j) = \left(\sum_{m=1}^{d} \left|x_{i,m} - x_{j,m}\right|^p\right)^{\frac{1}{p}}$$

Where $p \in \mathbb{R}^+$

Classification and Regression Rules

Given a query point q, the KNN algorithm proceeds as follows:

- Identify Neighbors: Find the set $\mathcal{N}$ f the k nearest neighbors in the training set, based on the chosen distance metric. Formally,

$$\mathcal{N} = argmin_{\substack{\subseteq\{1,\dots N\},\\ \{S|=k}} \sum_{i\in\mathcal{S}} d(\boldsymbol{x}_i, \boldsymbol{q})$$

- Prediction: Classification: Let the labels for the k nearest neighbors be $\{y_i : i \in \mathcal{N}\}$ The predicted class $\hat{y}$ is usually the majority class among these neighbors:

$$\hat{y} = mode\{y_i : i \in \mathcal{N}\}$$

  A weighted version often multiplies each neighbor's contribution by a function of its distance, e.g., $\omega_i = 1/(d(\mathbf{x}_i, \mathbf{q}) + \epsilon)$.

- Regression: The prediction is typically the average of the neighbor values:

$$\hat{y} = \frac{1}{k}\sum_{i\in\mathcal{N}} y_i$$

  As in classification, distance-weighted regression is also common:

$$\hat{y} = \frac{\sum_{i\in\mathcal{N}}\ \omega_i y_i}{\sum_{i\in\mathcal{N}}\ \omega_i}, \omega_i = \frac{1}{d(\boldsymbol{x}_i, \boldsymbol{q})^p + \epsilon}$$

Parameter k

The integer k governs how many neighbors influence the prediction. Too small a value (e.g., $k = 1$) can lead to an overfitted model (high variance), while a very large value might over smooth the boundary or predicted function (high bias). Optimal selection of k usually relies on cross-validation or empirical tuning.

Support Vector Machine (SVM) Classifier

Mathematically, consider a binary classification problem with labels $y_i \in \{-1, +1\}$ and feature vectors $x \in R^d$. An SVM seeks a decision boundary of the form

$$w \cdot x + b = 0$$

Where w is a weight vector orthogonal to the hyperplane, and b is a bias term. SVMs aim to maximize the margin around this hyperplane, subject to constraints that ensure correct classification (or controlled misclassification, in the soft-margin case).

The notion of margin is central to SVMs. The margin refers to the distance between the decision boundary and the closest training points from each class. These critical points are called support vectors. By maximizing the distance to the support vectors, SVMs improve their capacity to generalize.

When data are linearly separable, one can enforce that each point x_i is placed on the correct side of the hyperplane with a certain margin. Formally, for each i:

$$y_i(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1$$

This constraint ensures that all data points lie outside the margin of width $\frac{2}{\|\mathbf{w}\|}$. Consequently, maximizing the margin is equivalent to minimizing $\frac{1}{2}\|\mathbf{w}\|^2$ Interestingly, any data point not on the margin boundary (i.e., not a support vector) does not affect the solution.

$$y_i(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1$$

Hard-Margin and Soft-Margin SVMs

In the hard-margin scenario, we assume data are perfectly separable and no classification errors are allowed. The primal form of the optimization problem can be written as:

$$\min_{\boldsymbol{w},b} \frac{1}{2}\|\boldsymbol{w}\|^2 \text{ subject to } y_i(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1, \forall i$$

Although elegant mathematically, this situation is often unrealistic in real-world datasets that contain noise or overlap between classes.

To handle misclassifications in noisy or overlapping data, SVMs introduce slack variables $\xi_i \geq 0$. These variables allow certain margin violations, balancing them against margin width via a regularization parameter C. The corresponding primal form is:

$$\min_{\boldsymbol{w},b,\xi} \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{N} \xi_i$$

subject to

$$y_i(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0, \forall i$$

A high value of C penalizes misclassifications severely, pushing the SVM to correctly classify more points (potentially at the risk of overfitting). A lower C allows more slack in order to maintain a wider margin.

Kernal Trick

Most real-world problems are not strictly linear. The kernel trick was introduced to extend SVMs to handle non-linear decision boundaries. Instead of explicitly mapping data into a higher-dimensional feature space, we replace dot products $\mathbf{x}_i \cdot \mathbf{x}_j$ with a *kernel function* $\mathrm{K}(\mathbf{x}_\mathrm{i}, \mathbf{x}_\mathrm{j})$. A kernel function acts as an implicit inner product in some (potentially very high-dimensional) feature space, thus allowing the SVM to learn non-linear patterns efficiently.

Common kernel functions include:

- Polynomial Kernel**:**

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = (\boldsymbol{x}_i \cdot \boldsymbol{x}_j + 1)^p$$

- Radial Basis Function (RBF) Kernel**:**

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = exp\left(-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2\right)$$

- Sigmoid Kernel**:**

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = tanh\left(\alpha \boldsymbol{x}_i \cdot \boldsymbol{x}_j + c\right)$$

The dual form of SVM optimization in the kernelized setting replaces $\mathbf{x}_i, \mathbf{x}_j$ with $K(\mathbf{x}_i, \mathbf{x}_j)$, enabling the discovery of non-linear boundaries without computing explicit feature mappings.

ملخص الدراسة

يُعد تحسين إدارة أداء الموظفين ضرورة أساسية لتحقيق التميز المؤسسي، خاصة في القطاع العام، حيث تتطلب محدودية الموارد والتحديات البيروقراطية وتزايد توقعات المواطنين إيجاد حلول مبتكرة. تتناول هذه الأطروحة التحديات المتعلقة بتحسين إدارة أداء الموظفين في القطاع العام بمملكة البحرين من خلال دمج نماذج تنبؤية واتخاذ قرارات متقدمة قائمة على الذكاء الاصطناعي. اعتمدت الدراسة منهجية الطرق المختلطة الاستكشافية المتتابعة (Sequential Exploratory Mixed-Methods)، حيث بدأت بإجراء مراجعة منهجية للأدبيات ومرحلة بحث نوعية شملت مقابلات مع خبراء ومجموعات نقاش مركزة، مما أدى إلى تحديد 54 عاملاً مؤثرًا على الأداء، تم تنقيحها إلى 46 عاملاً رئيسًا ملائمًا للخصوصية السياقية للقطاع العام البحريني. تلا ذلك مرحلة كمية جُمعت فيها البيانات من خلال توزيع استبيان على عينة عشوائية بسيطة مكونة من (391) موظفًا في القطاع العام البحريني؛ وذلك لغرض تدريب نماذج التعلم الآلي. إن هذا الأسلوب المتتابع (الاستكشافي–النوعي ثم الكمي) ضمن أن يكون النموذج التنبؤي قائمًا على السياق التنظيمي الحقيقي والأطر النظرية الراسخة.

اعتمادًا على هذه العوامل المحددة والبيانات التاريخية للأداء، تم تطوير نظام تنبؤي يعتمد على الذكاء الاصطناعي. وأظهرت النتائج التجريبية أن هذا النموذَج قادر بدقة على التنبؤ بنتائج أداء الموظفين وتحديد الفجوات في الأداء، وقد حقق نموذج آلة المتجهات الداعمة (SVM) دقةً بلغت (92.51%) في التمييز بين الموظفين ذوي الأداء المرتفع والمنخفض، ما يؤكد فعالية النموذج المقترح. كما أظهرت النماذج التصنيفية الأخرى قدرات تنبؤية قوية، في حين أسهم استخدام الخوارزميات الجينية (Genetic Algorithms) في تحسين الأداء التنبؤي للنموذج من خلال الاختيار الأمثل للمتغيرات الأكثر تأثيرًا. ومن أجل ضمان قابلية التطبيق العملي لمخرجات النموذج، تم استخدام تقنيات الذكاء الاصطناعي القابل للتفسير (XAI)، وأبرزها تقنية قيم شابلي التفسيرية المضافة (SHAP)، مما ساهم في توضيح الأهمية النسبية لكل عامل من عوامل الأداء وترجمة التنبؤات إلى توصيات وسياسات استراتيجية قابلة للتنفيذ من قبل إدارة الموارد البشرية.

تقدم هذه الأطروحة نموذجًا مبتكرًا يمكن تعميمه وتطبيقه في سياقات مماثلة، حيث يربط بين الممارسات التقليدية لإدارة الموارد البشرية وأحدث تطبيقات الذكاء الاصطناعي، مما يتيح تحويل التقييمات التقليدية للأداء إلى عمليات مستمرة مدعومة بالبيانات. كما تُبرز الدراسة أهمية الاعتبارات الأخلاقية في هذا السياق، خاصة فيما يتعلق بالعدالة، والشفافية، وتخفيف التحيز في استخدام الذكاء الاصطناعي لتقييم الموظفين. وانطلاقًا من هذه النتائج، توصي الدراسة بوضع سياسات واضحة للحوكمة وأخلاقيات الذكاء الاصطناعي، مع تعزيز الرقابة البشرية والشفافية، وتطوير البنية التحتية للبيانات الخاصة بالموارد البشرية، وتحديث سياسات إدارة الأداء لتشمل الرؤى المستمدة من الذكاء الاصطناعي، مع التركيز على استقلالية الموظفين وقدرتهم على التكيف. كذلك، أوصت الدراسة بالتحول نحو تغذية راجعة مستمرة ومستنيرة بالبيانات، وتنمية القدرات المؤسسية من خلال التدريب على استخدام وأخلاقيات الذكاء الاصطناعي وإدارة التغيير، وضمان توافق مبادرات الذكاء الاصطناعي مع الاستراتيجيات الوطنية الرقمية لمملكة البحرين كرؤية البحرين 2030 وتحديثاتها 2050.

جـامعة البحــرين

كلــية إدارة الأعمـــال



تعزيز إدارة أداء الموظفين من خلال نماذج التنبؤ واتخاذ القرار المدعومة بالذكاء الاصطناعي

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الدكتوراه في تحليل الأعمال

إعـــداد

توفيق محمد صالح السباعي

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مملكـــة البحـــرين

مايو 2025م