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IMPACTS OF HRM AND KNOWLEDGE MANAGEMENT ON ORGANISATIONAL PERFORMANCE IN MANUFACTURING INDUSTRY

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ABSTRACT

Human resource management and knowledge management are considered to be key aspects in the manufacturing industry, mainly owing to the reason that both provide organisations with the benefit of strategic approaches that helps in making better decision-making and implementing better innovation. The focus of the current study is on analysing how the HRM and KM impacts the organizational performance in the manufacturing industry. The KM is the mediator that assess the relationship between the HRM and organisational performance in the manufacturing industry. Theories such as the Knowledge-Based View (KBV) and the SECI model highlighted that knowledge is an imperative critical organisational resources and source for sustainable competitive advantage, along with ensuring that conitnous knowledge is created. Data was gathered from 203 respondents who were Supervisors, Administrative Staff, Middle Management staff working in 13 leading manufacturing firms in pakistan. The impacts were estimated by making use SMART partial least squares structural equation modelling (PLS). The results highlight that HR has a significant impact in delivering organisational outcomes in relation to the knowledge development. Moreover, the result further reveal that HRM practices impacts on KM in manufacturing industry, along with KM showing significant impact on organisational performance in manufacturing industry. The study solely focus on quantitative analysis, highlighting that the relationship of HRM and organisational performance is affected by the KM as a mediator. The recommendations of the study are to improve knowledge usage mechanisms, invest in technology for KM, strengthen the HRM practices further, develop leadership commitment within the organisation, monitor the impact of KM on the organisational performance and ensure that a learning organisation environment is encouraged.

***Keywords**: Human Resource Management, Knowledge Management, Organisational Performance, Manufacturing Industry.*

1. INTRODUCTION

1.1 Background of the Study

As per Cania (2014), Human Resource Management (HRM) is the strategic approach being employed in the management of human capital in an organisation with a primary aim of optimising human performance with a view to enhancing the organisation's goals. As regards the manufacturing industry, the main HRM aspects therefore entail reciting, training and training a well skilled workforce to operate complex machineries and clock production schedules. Furthermore, according to Albrecht et al. (2015), HRM prioritises the development of employee engagement, ensuring that there is utmost compliance with labour laws and also enacting policies that advocate workplace safety and process efficiency. Achieving optimised productivity with a competitive edge in the manufacturing sector goes hand in hand with organisation's goals and workforce's capabilities when organisations are aligned.

According to Abubakar et al. (2019), Knowledge Management (KM) is about the organised process of identifying, transferring, and exploiting organisational knowledge for the purposes of productive decision making and innovation. With respect to the manufacturing, its implementation means documenting operational processes and sharing best practises along with assimilating the technological advacement that will help in laying out the production process. Furthermore, it also facilitates tacit knowledge (which implies the expertise of seasoned employees has passed across the organisation). According to De Long and Davenport (2003), the new employees mostly lean on seasoned employees to learn and to work with organisational goals. In addition to providing ways to reduce redundancies and operational error, KM provides a means to continuously improve from the collective expertise and establishing a culture of learning and collaboration.

According to Alegre, Sengupta and Lapiedra (2013), the integration of HRM and KM tends to significantly affect the organisational performance in various industries (such as healthcare, retail and manufacturing), which focuses on efficiency, innovation and adaptability are important. HRM emphasises on managing people as strategic assets with employers ensuring that effective recruitment, training and motivation is carried out to meet the organisational goals. Supporting the prior notion, Joia and Lemos (2010) asserted that KM focuses on the organisational knowledge (which are explicit data and tacit expertise) to capture, share and use the knowledge in an effective way. It is imperative to note that the interplay between the domains create a synergy which improves the workforce capabilities, develops innovation and drives operational excellence.

In term of HRM perspective, the development of culture of continuous learning and development is important in the manufacturing industry for the organisations to remain competitive. Li (2022) asserted that employees are equipped with up-to-date skills and knowledge which helps to adapt to new technologies. It also helps with implementing advanced production techniques and maintain the product quality. KM helps bridge the aforementioned bridge by offering systems and processes to store and share critical knowledge across teams, along with preventing knowledge and improving decision-making aspect (Luong, 2023). An example that can be used to understand the notion is the documentation of best practices for machine maintenance or safety protocols which allows consistency and decreases downtime that occurs due to preventable errors.

According to Malik, Froese and Sharma (2020), the impact of HRM and KM integration is on innovation and problem-solving. The HRM practices (team-building, employee engagement initiatives, promoting collaboration) helps to create an environment where knowledge sharing thrives. The KM systems allows this kind of collaboration by providing platforms for idea exchange and cross-functional learning. Lei, Khamkhoutlavong and Le (2021) asserted that the collaboration of HRM and KM improves innovation as employees leverage share insights to develop solutions to complicated production challenges, improve efficiency and design new products.

Apart from this, the HRM and KM also contribute towards an improved employee retention and satisfaction that are important to understand in organisational performance. Al-Emadi, Schwabenland and Wei (2015) asserted that HRM strategies emphasises on training, career development and recognition which allows employee to feel valued and invested in. when KM is integrated into the strategies, employees have access to the information and tools that they need to succeed in their job role. It is also imperative to note that organisations also get a chance to create an environment where employees are productive, motivated and loyal. When the high retention rate increases, it helps in reducing the recruitment costs and preserve institutional knowledge (De Long and Davenport, 2003). This aspect is particularly valuable in manufacturing industries that is dependent on skilled labour.

1.2 Problem Statement

The manufacturing industry comprises of rapid technological advancements, intense competition and a dynamic global market. Turner (2024) asserted that to thrive in aforementioned environment, organisations should consistency improve their operational efficiency, innovate and adapt to changing demands. However, it is imperative to note that achieve the aforementioned objectives tend to reveal significant challenges (mainly in managing human resources and organisational knowledge). Organisations in the manufacturing industry tend to struggle to recruit and retain a skilled workforce, align employee competencies with technological advancements and develop a culture of continuous learning and innovation. Schmitt, Borzillo and Probst (2012) stated that the effective capture, sharing and application of organisational knowledge remains a persistent issue, with critical information being focused in silos or lost due to employee turnover.

There is lack of integration among HRM and KM which aggravates the aforementioned challenges leading to inefficiencies in production processes, reduced innovation capacity and diminished competitiveness. An example that can be stated here is the insufficient training and development programs fail to equip employees with the skills required to operate advanced machinery or implement lean manufacturing techniques. There is also the absence of robust KM systems which affects the sharing of best practices and lessons learned, resulting in repeated operational errors and missed opportunities for improvement. The current study will focus on resolving the aforementioned challenges in relation to the manufacturing industry.

1.3 Gap Analysis

Although the importance of both HRM and KM for organisational performance is increasingly understood, they are inadequately incorporated into most manufacturing firms. Nevertheless, theoretical and empirical studies lay the groundwork for high benefits from this integration, like better operational efficiency, better innovation, and higher adaptability. But in actual, there remains a few gaps that still exist in the HRM and KM implementation and utilisation in the manufacturing.

Among all, the alignment between HRM strategies and KM practices is the area of a great need to being bridged. HRM is concerned with recruiting, training and retaining good employees, but these HRM efforts are often unconnected with KM systems designed to capture and share organisational knowledge. This misalignment leads to a disjointed method where employees may possess the skills; however, they do not have access to the information and best practices they need to achieve maximum productivity and innovation. Thus, for example, there are no mechanisms for transferring the tacit knowledge from trained to newer staff in the training programs, and thus when experienced staff leave the organisation knowledge is lost.

A gap exists with the inadequacy in use of technology to link HRM and KM. There is much underutilisation of advanced KM systems such as knowledge repositories and collaboration platforms in many of the manufacturing firms. Often, this is because of a lack of investment, and or non-integration of these technologies with HRM tools such as performance management systems or learning management systems. As a result, employees find it difficult to tap into the information they need or to spread the insights around to other teams and departments, so organisations are missing opportunities for creating an environment of continuous learning and innovation.

1.4 Research Objectives

The research objectives of the study are:

- To determine the significance of HRM on organisational performance
- To assess the association of knowledge management with organisational performance
- To analyse the impacts of HRM and knowledge management on organisational performance in manufacturing industry

1.5 Research Questions

The research questions of the study are:

- What is the significance of HRM on organisational performance?
- What is the association of knowledge management with organisational performance?
- What is the impacts of HRM and knowledge management on organisational performance in manufacturing industry?

1.6 Research Significance

1.6.1 Theoretical Significance

This research contributes from a theoretical perspective to this body of knowledge by exploring the influence of the interaction of KM and HRM on Organisational Performance (OP) in the manufacturing industry. HRM and KM are well developed subjects of study, but the combined study of the disciplines has been underexplored, especially with respect to the manufacturing context. The research hopes to fill an important gap in the literature by looking at this relationship in order to understand how the alignment of HRM and KM can be synergies leading to more effective workforces, enhanced innovation, and adaptability.

In addition, the study provides theoretical frameworks by relating HRM practices (recruitment, training and retention) to KM processes (knowledge capture, sharing and application). Thus, it provides a conceptual basis for appreciating the ways in which these functions are complementary individual elements in promoting organisational success. Furthermore, the study introduces manufacturing specific variables such as technological advances, operational efficiency and lean practices in the discussion of relevance of the hybrid of HRM and KM. These contributions can provide basis for future studies and development of additional more holistic models to capture dynamic needs of modern organisations.

1.6.2 Practical Significance

As a practical contribution, this work provides insights for managers and decision-makers in the manufacturing industry. The study identifies best practices for integrating HRM and KM and also provides a roadmap for organisations to maximise their human and knowledge resources. Also, it makes evident that HRM strategies (e.g. workforce development, performance management) should be aligned with KM approach (e.g. knowledge repositories, collaborative platforms) and so on. All of this alignment can make organisations improve employee productivity, reduce operational errors and encourage a culture of continuous improvement.

On the other hand, the research investigates the part played by technology in the integration of HRM and KM, advocating for organisations to make investments in sophisticated tools and systems which facilitate knowledge exchange and employee growth. The study provides manufacturing firms with strategies for retaining institutional knowledge, and helping avoid losing knowledge due to employee turnover or inadequate training, addressing practical challenges on this front.

These results can provide policy prescriptions within organisations, suggesting frameworks that aid the integration among HRM and KM. Incorporating these frameworks can enhance decision making, the firms' innovation capacity, and the capacity to respond to the market's changes especially in an ever-changing manufacturing environment thus assuring long term competitiveness. Ultimately, the research narrows the gap between theory and practice by explaining how HRM and KM may be deployed for superior organisational performance.

2.Literature Review

2.1 HRM in the manufacturing industry

Global economic pressures, advances in technology, and workforce diversity have led to a considerable transformation in the role of HRM in the UK manufacturing industry. The UK economy's apparent saviour has been the manufacturing sector, and in recent years it has had its fair share of challenges, whether that's the implications around Brexit, supply chain issues or workforce shortages.

2.1.1 Talent Acquisition and Retention

Talent acquisition and retention are high-priority challenges for the manufacturing industry, particularly for hiring skilled and semi-skilled labour (Wayne, 2018). An ageing workforce and a lack of interest among younger generations in manufacturing careers are widening the talent shortage, according to studies. HR managers have begun relying more on apprenticeship programs and partnerships with educational institutions to trigger a pipeline of skilled workers to combat these issues (Bland, 2019). In addition, the strategy to attract talent is also highlighted which effective employer is branding. Research shows that those companies that offer decent compensation, clear career paths and training opportunities are more likely to retain employees.

The demanding nature of the jobs, which are routinely repetitive work and long hours, also influences other retention strategies (Demerouti and Bakker, 2023). Companies need flexible work arrangements and an improvement in workplace conditions to reduce turnover rates. HR practices that emphasise employee well-being (e.g., mental health support and ergonomic interventions) have taken off.

2.1.2 Employee Engagement and Productivity

In the manufacturing sector, employee engagement has a strong relationship to productivity. Studies have shown that engaged workers are more likely to contribute to the pursuit of organisational goals as well, have low absenteeism and deliver a higher quality of output (Gupta and Sharma, 2016; Osborne and Hammoud, 2017; Smith and Bititci, 2017). Manufacturing HR managers have come up with many different ways to boost engagement including recognition programs, engaging employees in decision-making, and training employees in new skills.

Further, the literature also points to the need to develop a culture of respect and inclusion, in settings where workers represent diverse backgrounds (Shore, Cleveland and Sanchez, 2018; Mor Barak, 2015). With international recruitment leading to a more and more multicultural workforce, HR needs to address the cultural sensitivity of everything they do as well as communication barriers. Furthermore, performance management systems that ensure alignment between employees' goals and organisational objectives are essential in maintaining employee engagement levels (Mone, London and Mone, 2018).

Engaged employees are a critical driver for organisational performance, as engaged employees outperform employees who are not engaged. Fostering engagement is a huge job for HRM, which does so through initiatives that increase employees' sense of job satisfaction, meaningful work, and belonging (Chakraborty, Sharada and Anand, 2024). Existing literature stresses that HR practices including recognition programs, transparent communication & participative decision making lead to increases in engagement (Rana, 2015; Osborne and Hammoud, 2017; Karam et al., 2017). They also have lower absenteeism and turnover rates meaning they save you money, but they also make your performance metrics look better.

2.1.3 Technological Adaptation and Workforce Development

Industry 4.0 has completely changed the manufacturing sector integrating digital technologies like automation, robotics and artificial intelligence (Javaid et al., 2021). All these technological advancements have changed the workforce requirements. The HR department is important in making the transition possible by organising training programs and also fostering a learning-oriented culture. Technology can increase operational efficiencies but it can also be challenging when people suitable for older jobs, perhaps historically unskilled, have to adapt to technology (Mindell and Reynolds, 2023). To ensure smooth integration of the technology, HR professionals will continue to have to balance the introduction of technology with their support systems.

2.2 Importance of HRM on organisational performance

In different sectors, organisations have made HRM a core of competitive advantage achievement. Extensive work has been conducted on the relationship between HRM practices and organisational performance, whereby strategic HR contributes to raising productivity, stimulating innovation, and in general achieving organisational success (Singh, 2018; Alfawaire and Atan, 2021; Anwar and Abdullah, 2021).

2.2.1 Strategic Human Resource Management (SHRM)

SHRM is to ensure that HR policies are in line with the company's goals and hence make sure human capital participates immediately in decisions related to performance outcomes. According to Eneh and Awara (2016), this is more about long-term planning versus transactional HR practices, and concentrating on workforce capabilities that produce business results. Some studies showed that organisations with fully integrated HR strategies, out of those with fragmented HR functions, tend to be more financially successful, more customer-satisfied, as well as more differentiated in the market (Genchel and Mårtensson, 2016; Edger, 2016; Alvesson, 2022). A major concept in SHRM is the Resource Based View (RBV) that maintains human resource is a valuable, rare, inimitable and non-substitutable resource (Sharma and Limaye, 2021). Training, performance appraisal, and succession planning as HRM practices are identified as means for developing and keeping these key resources in place, in order to create organisational resilience and adaptability.

2.2.2 Talent Management and Organisational Performance

It is of great importance to sustain organisational performance which includes recruitment and development and retaining of high potential employees which comes under talent management (Al Aina and Atan, 2020). This is achieved by applying talent management strategies that see the right people in the right fit, adding value to their careers and skills and vice versa. HRM practices such as competency-based hiring, personalised training modules and performance-linked incentives supplement the practice of workforce optimisation. Studies show that investing in talent management results in organisations that are more innovative, faster at seeing through projects, and have better customer service (Sparrow et al., 2015; Pandita and Ray, 2018; Van Zyl, E.S., Mathafena, R.B. and Ras, J., 2017). Talent management and the alignment of individual and organisational goals go hand in hand, not only increasing organisational performance but also inciting employee loyalty and commitment.

2.2.3 Organisational Culture and HRM Practices

HRM practices have a very significant effect in creating organisational culture which is a strong predictor of performance (Botelho, 2020). A strong, adaptive culture merges employee behaviour with organisational objectives, encourages collaboration, and generates innovation. HR helps to build this culture by embedding shared values and norms, through how one onboard, how one continuously develop leadership and provide feedback. Trust, accountability and empowerment are suggested in the literature as being characteristics of a high-performance culture (Hakanen, Häkkinen and Soudunsaari, 2015). Team building exercises, conflict resolution training, and diversity and inclusion initiatives are some of the HR interventions that contribute to a cohesive work environment in support of sustained performance. Alternatively, a miss-aligned culture can stall organisational advance, hence the role of HR is crucial in continuous cultural iteration.

2.3 Association of knowledge management with organisational performance

In the current age of fast-changing technology and dynamic business environment, KM has emerged as a critical determinant of organisational performance. The systematic processes through which organisations create, share, use and manage knowledge resources to achieve strategic objectives are KM.

2.3.1 Theoretical Underpinnings of Knowledge Management

KM is grounded in theory, for example, the Knowledge-Based View (KBV) of the firm, which views knowledge as a critical organisational resource and source for sustainable competitive advantage (Duarte Alonso et al., 2022). Tacit knowledge, embedded in the employee's expertise and experience, is not only more valuable but is also more difficult to imitate than explicit knowledge, which can be easily documented and transferred. Institutionalising two types of knowledge appears to lead to superior performance. KM also has another key framework which is the SECI model (Socialisation, Externalisation, Combination, and Internalisation) (Natek and Zwilling, 2016). The dynamic ways, in which tacit and explicit knowledge interact over time to create continual knowledge, are exposed by the model. The cyclical process is important in forcing innovation, adaptability in competitive market and therefore, KM is critical for business success.

2.3.2 Knowledge Creation and Organisational Performance

Knowledge creation is at the core of KM and is a critical performance function. The studies suggest that organisations with firm knowledge creation capabilities can innovate and accelerate response to shifting demands faster (Grimsdottir and Edvardsson, 2018; Goyal, Ahuja and Kankanhalli, 2020). In other words, new ideas are to be created, and existing ones repurposed (or refined) knowledge to address the changing needs. The studies point out that collaborative projects, brainstorming sessions, and cross-functional teams are KM practices that help create knowledge (Dussart, van Oortmerssen and Albronda, 2021; Ewim et al., 2024). In addition, it is also necessary to have a leadership commitment to promoting a knowledge-oriented culture. Risk-taking and experimentation are encouraged by leaders who create an environment where different solutions are being created and performance is improved.

2.3.3 Knowledge Sharing and Collaboration

Knowledge sharing, being a component of KM is itself an integral factor in organisational efficiency and effectiveness (Abualoush, Bataineh and Alrowwad, 2018). This also refers to the ability to stretch the information over departments, teams and individuals for improving decision-making and problem-solving. Knowledge sharing prevents redundancy, shortens the project timeline and also improves the quality of outputs (Tyagi et al., 2015). Strong organisational culture is the unforgotten and the most important factor that facilitates knowledge sharing. Key enablers here are trust, transparency and open communication while employees have the higher urge to share knowledge in environments where they feel valued and supported (Dahiya, 2023). Moreover, systems of rewards and training programs employed by HR continue to be deemed the most essential element that motivates others to participate in knowledge-sharing initiatives.

2.3.4 Knowledge Retention and Continuity

Sustaining organisational performance requires retention of knowledge in the face of workforce turnover and demographic changes (Sumbal et al., 2017). Maintaining critical knowledge that is important to the operation ensures that knowledge of the organisation stays intact so that operational disruption is forestalled. Conventional strategies for retaining institutional knowledge include documentation, mentoring programs and knowledge repositories (Dewah and Mutula, 2016). Succession planning and structured exit interviews have been highlighted by studies as key means of retaining the tacit knowledge of exiting employees. Those organisations that do not retain knowledge face innovation and performance setbacks as the backing is not made to integrate it into their overall HR and operational strategies.

2.3.5 Innovation and Competitive Advantage

One of the most tangible benefits of effective KM is innovation; knowledge is the resource out of which new products, services, or processes can be developed (Migdadi, 2022). KM allows organisations to bring together disparate sources of knowledge in ways that suppress creativity and collaboration. For example, technology-driven KM tools such as knowledge portals, intranets and artificial intelligence systems enable real-time knowledge exchange and analytics reducing innovation cycles (Migdadi, 2022). Those who treat KM as part of their innovation strategy, however, continue to outpace the competition in dealing with market trends and meeting customer needs.

2.4 KM as a mediator between HRM and OP

Currently, the transfer of KM as a mediator between HRM and OP is a matter of academic and managerial discourse. HRM and KM are essential for enabling the organisation to succeed, with HRM setting the building blocks of human capital and KM optimising the utilisation and flow of knowledge resources of the organisation (El-Farr and Hosseingholizadeh, 2019). The focus of this literature review is on analysing the interplay between these domains where KM plays a role in amplifying HRM's effect on OP by way of knowledge creation, sharing and retention processes.

2.4.1 Theoretical Framework: Linking HRM, KM, and OP

There is a well–documented relationship between HRM and OP, in that HRM practices including recruitment, training, and performance management directly affect employee productivity and organisational outcomes (Sabiu et al., 2019; Mira, Choong and Thim, 2019). However, when the role of KM is considered as a mediator, it sheds interesting light on how HRM practices are translated into superior performance. A theoretical foundation for this research is the KBV of the firm which argues that knowledge is the firm's critical organisational resource that yields a sustainable competitive advantage.

KM is a bridge that HRM uses to make the most out of employees' skills, competencies and experience (Gope, Elia and Passiante, 2018). KM practices being embedded into HRM functions make it possible for an ecosystem to be created within the organisations that result in the generation and sharing of knowledge in the pursuit and application of strategic objectives. The approach is integrated such that the contribution of human capital improves the organisation's performance.

2.4.2 HRM Practices as Enablers of Knowledge Management

KM practices require foundational support from HRM. Knowledge from the HRM policies and strategies facilitates the acquisition and dissemination of knowledge from the organisation's environment (Donate and Guadamillas, 2015). For example, a recruitment and selection system can be designed to attract those with the trait of sharing knowledge and collaborating with others. In the same way, training and development programs enable the employees with the tools and techniques to make effective knowledge dialogue.

Another HRM practice that can drive KM is performance appraisal systems whereby some specific knowledge-sharing behaviours are incentivised (Andreeva et al., 2017). An organisation that promotes collaboration is also one that rewards employees for contributing to knowledge repositories or for mentoring peers. Furthermore, collective HR policies that encourage team work as well as cross-functional projects, support the flow of knowledge through different organisational levels as well as across departments, which in turn promotes innovation and good-quality decision-making.

2.4.3 Knowledge Management Processes Mediating HRM and OP

KM processes, including knowledge creation, sharing, and retention, mediate the relationship between HRM and OP by transforming human capital into actionable insights and innovation.

Knowledge Creation

HRM practices, such as brainstorming sessions, innovation hubs, and using collaborative tools, stimulate idea generation. The interaction between tacit and explicit knowledge in continuously creating knowledge is captured by the SECI model. Highlighting Prominence of HRM in Contemporary Organisations (Farnese et al., 2019). An empowered employee contribute towards these goals, through their ideas when HRM fosters such an environment and such employees are nurtured within the organisation towards their improvement and growth (Quader, 2024). They can be facilitated to come up with unique solutions in the light of synergy resulting in fostering competitiveness and operational efficiency.

Knowledge Sharing

Knowledge dissemination is one of the key components of spreading the benefits of HRM practices across the organisational levels. HRM initiatives in this process include knowledge-sharing platforms created, mentoring programs encouraged etc. Research has shown that knowledge-sharing behaviours such as obviating duplication of effort, enhancing teamwork and accelerating problem-solving all lead to organisational performance (Singh and Gupta, 2023; Mills, 2016; Saxena, 2015).

Knowledge Retention

That valuable organisational knowledge is being preserved, despite employee turnover. Succession planning, knowledge documentation and the setup of centralised knowledge repositories constitute HRM practices that protect institutional knowledge (Iyiola, 2024). Knowledge retention helps to maintain processes and strategies with less disruption and with more or less the same levels of performance.

2.5 Literature Gap

Despite substantial research on the role of KM and OP, little work has been done to investigate the mediating role of KM in between HRM and OP. Previous literature has analysed HRM practices and their direct impact on operational performance or analyse KM as an independent driver of performance (Gope, Elia and Passiante, 2018; Kianto, Sáenz and Aramburu, 2017). Nonetheless, how HRM practices can enable KM processes to facilitate OP has not received much attention. This gap represents an opportunity to further explore how KM might be integrated into HRM frameworks to produce superior outcomes.

Most knowledge management research focuses on traditional human resource management practices like recruitment, training, and performance management, and ignores how these practices contribute to the establishment of knowledge management processes. For example, studies that recognise the significance of training programs often fail to particularly examine how such programs foster knowledge creation, sharing, or retention (Park and Kim, 2018; Dee and Leisyte, 2017). Similarly, the motivational impacts of performance appraisals have been studied, but rarely connected to the promotion of knowledge-sharing behaviours. An absence of integration in the literature prevents understanding how HRM practices target KM to achieve sustainable organisational performance in dynamic environments.

The KBV for the firm underscores the strategic value of knowledge, even as it is not fully applied in the role of a mediating factor between HRM and OP. Most studies either consider KM as an independent variable which affects OP or study its role in innovation and competitive advantage without clearly linking it to HRM practices (Alkhazali, Aldabbagh and Abu-Rumman, 2019; Al-Sa'di, Abdallah and Dahiyat, 2017). In addition, frameworks such as the SECI model are very widely discussed in KM literature but are under-researched in the application of HRM contexts. The disconnection between HRM and KM reveals the need to fully understand how HRM practices activate and sustain KM processes to support OP.

3. Conceptual model development and hypothesis

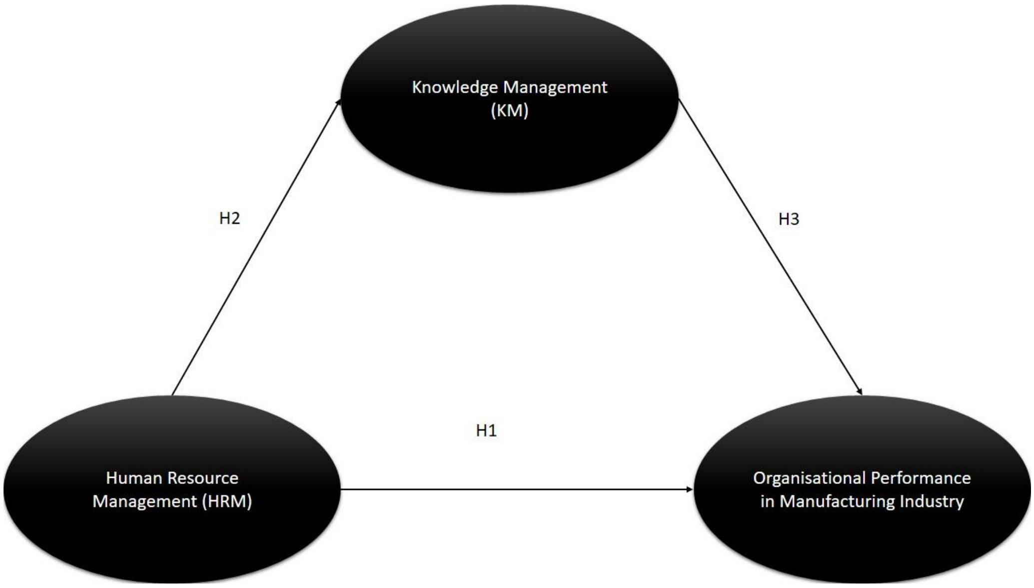


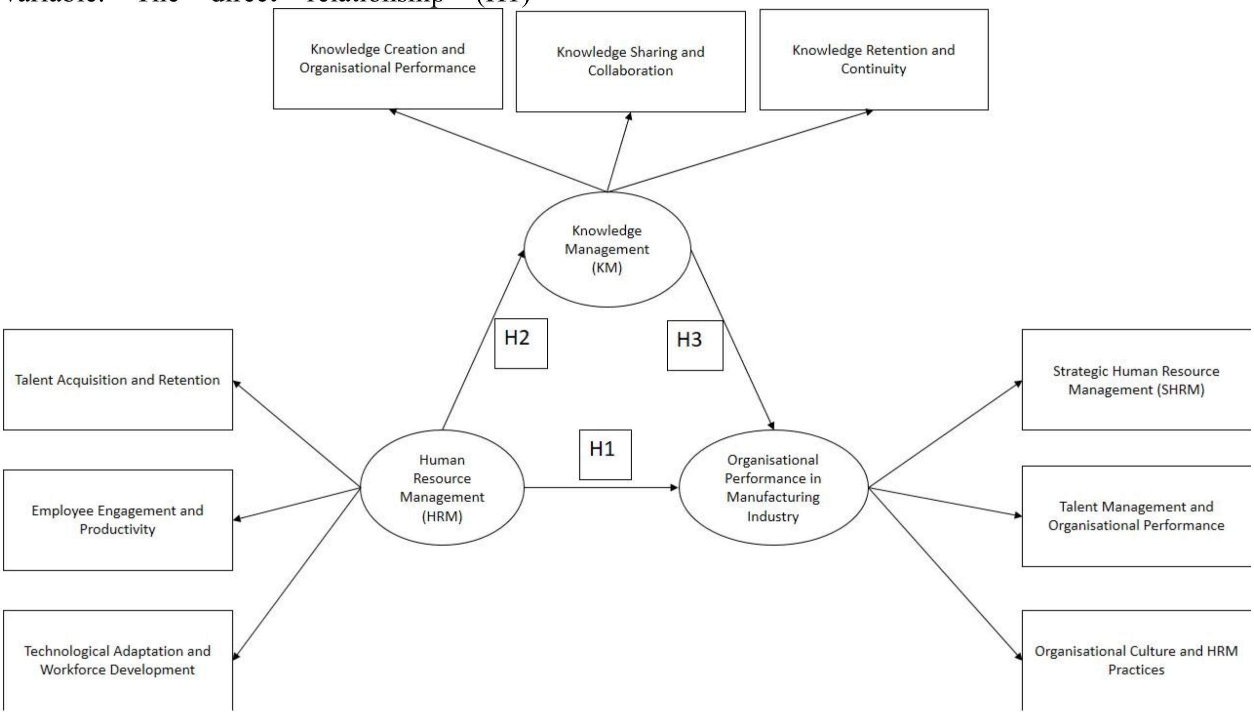
Figure 1 - Conceptual Model

Independent Variable – HRM
Mediator – Knowledge management
Dependent Variable – Organisational performance in manufacturing industry

3.1 Summary of the Relationship of Direct Variable Effect

The model illustrates the relationship between Human Resource Management (HRM) as the independent variable and Organisational Performance in the Manufacturing Industry as the dependent variable. The direct relationship (H1) signifies that effective HRM practices, such as talent acquisition, training, performance management, and employee engagement, positively influence organisational performance by improving productivity, innovation, and operational efficiency.

Additionally, Knowledge Management (KM) acts as a mediator, highlighting how HRM contributes to better organisational performance through the generation, sharing, and application of knowledge within the organisation (H2 and H3).



3.2 Hypotheses

Based on the aforementioned theories and literature carried out in previous chapter, the conceptual model was developed shown in figure 1. The main hypothesis of the study are:

H1: There is a significant impact of HRM on organisational performance in manufacturing industry

H2: There is a significant impact of HRM practices on knowledge management in manufacturing industry

H3: Knowledge management has a significant impact on organisational performance in manufacturing industry

3.3 Mediation and Moderation Analysis

Mediation Analysis (Indirect Effect)

Mediation occurs when the relationship between HRM and organisational performance is explained (partially or fully) by KM.

To analyse mediation:

Step 1: Establish that HRM directly influences organisational performance (H1).

Step 2: Confirm HRM significantly influences KM (H2).

Step 3: Test whether KM significantly impacts organisational performance (H3).

Step 4: Examine if the direct relationship (HRM → Organisational Performance) weakens or disappears when KM is introduced into the model.

Statistical tests (e.g., Sobel test, bootstrapping in SEM) can quantify the indirect effects of KM.

Moderation Analysis

Communication is introduced as a moderator to enhance the HRM-KM relationship. Moderation implies that the strength or direction of the HRM → KM link changes depending on the level or quality of communication within the organisation.

Testing Moderation:

Interaction terms (HRM × Communication) in regression analysis assess the moderating role of communication.

A significant interaction effect confirms that communication improves the HRM → KM relationship.

3.4 Communication Moderating the Relationship

When communication is strong and effective, it acts as a catalyst in the HRM-KM dynamic:

Clear and frequent communication fosters better collaboration, sharing of best practices, and alignment of knowledge goals with organisational objectives.

For example:

HRM initiatives like training programs and performance feedback are more effective when employees understand their purpose and how knowledge-sharing benefits individual and team performance.

Good communication mitigates barriers such as knowledge silos or resistance to change, further strengthening KM practices.

Thus, organisations with robust communication channels are likely to see amplified benefits from HRM and KM, culminating in superior organisational performance.

4. Research Methodology

4.1 Research Paradigm

The research paradigm guiding this study was positivism, which emphasised objective, observable, and measurable aspects of reality. Positivism was rooted in the belief that social phenomena, like organisational performance, HRM, and KM, was studied using the same scientific methods as natural sciences. The study's aim to study cause and effect relationships among HRM practises, KM and organisational performance in the manufacturing context made this paradigm fit.

In positivism, in the first place the focus was detached and objective, attending to the tangible data, which are quantifiable. This approach enabled statistical analysis of the validity of the proposed hypotheses (H1, H2, H3) and further ensured the generalisation of the findings to a wider scope of manufacturing firms.

The ontology of the study was objectivism, that is, social realities such as organisational performance and the effects of HRM and KM exist outside and independently of individual perceptions. HRM practises, KM and organisational performance were treated as measurable constructs, separated from the subjective interpretations of respondents.

Organisational performance metrics (e.g. productivity, profitability) and effectiveness of HRM and KM were taken as having a real, observable impact — uninfluenced by personal and cultural biases.

The research was underpinned by objectivism which regarded these constructs as external reality and, thus enabling the study of these constructs using structured and standardised methods like surveys. By adopting this perspective, the researcher was able to examine relationships between variables consistently and replicable across different manufacturing contexts.

4.2 Research Design

It was a primary quantitative design used to collect and analyse numerical data that would examine the relationship between HRM practises, knowledge management (KM), and organisational performance in the manufacturing industry. However, as the design was selected to offer an objective, measurable and statistically analysable insight into the proposed hypotheses, this design was considered to be optimum. The study focused on quantifiable data, so as to formulate empirical evidence about the causal relationships among the studied variables. This made this particular study ideally suited to a quantitative approach since standardised responses were able to be collected from a large number of participants. This structured form of the survey ensured that all information collected were uniform, thus reducing potentials of introducing bias on interpretations of the information. This approach enabled the researcher to identify patterns, verify correlations and make conclusions that are both valid and generalised to the population of all manufacturing firms.

4.2.1 Causal and quantitative

In this study, the influence of the interrelationships of HRM practises, KM and organisational performance in the manufacturing industry was investigated using a causal and quantitative research design. To gather measurable data to support statistical analysis, the quantitative approach was adopted, and the causal design which was employed to analyse the causal relations involved in causal hypotheses.

The study aimed to test the following hypotheses:

H1: There is a significant impact of HRM on organisational performance in the manufacturing industry.

H2: There is a significant impact of HRM practices on knowledge management in the manufacturing industry.

H3: Knowledge management has a significant impact on organisational performance in the manufacturing industry.

The combination of causal and quantitative methods provided a systematic way to explore these hypotheses and draw empirical conclusions about the relationships between the variables.

The causal research design was central to this study because it focused on understanding how HRM practices and KM influenced organisational performance. Causal research investigates not only whether relationships exist between variables but also how these relationships manifest. For instance:

To test H1, the study explored how specific HRM practices, such as recruitment, training, and performance evaluation, impacted key performance indicators (KPIs) like productivity and profitability.

For H2, the study examined the extent to which HRM practices fostered effective KM processes, such as knowledge sharing, documentation, and employee access to critical information.

Regarding H3, the research investigated whether improved KM practices directly enhanced organisational performance metrics, such as operational efficiency and innovation.

By focusing on these cause-and-effect relationships, the study aimed to provide actionable insights for manufacturing organisations to optimise HRM and KM practices for better performance outcomes.

4.2.1.1 CFA Confirmatory Factor Analysis

To validate the measurement model, the Confirmatory Factor Analysis (CFA) was conducted, and that the constructs used in this study are reliable and valid. This is a statistical testing technique to cheque out the goodness of fit of a hypothesised measurement model to a theory derived measurement model. In this research, CFA was conducted to evaluate the relationships between observed variables (survey items) and their corresponding latent constructs:

The relationships between HRM practises, KM and organisational performance.

4.3 Questionnaire/instrument

4.3.1 Adopted

The questionnaire was adopted from the study of Kokkaew et al. (2022).

4.3.2 Construct (variable)

The questionnaire was structured into three main sections, each corresponding to one of the study's key constructs:

HRM Practices: This section included questions on recruitment, training, performance appraisal, and employee motivation, tailored to reflect practices commonly employed in the manufacturing sector.

Knowledge Management: Items focused on processes such as knowledge sharing, accessibility, and documentation, assessing the effectiveness of KM initiatives within organisations.

Organisational Performance: Questions measured performance indicators such as productivity, innovation, operational efficiency, and profitability.

4.3.3 Items (no of questions)

14 items for HRM, 8 items of KM and 6 items of OP

4.3.4 Likert Scale

Each item was rated on a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing for the quantification of respondents' perceptions and facilitating the use of advanced statistical analyses like Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

4.4 Sampling frame work/Sampling Size

To perform SEM, Hair et al. and Schumacker and Lomax suggested that the sample size of respondents should be greater than 160 or at least 10–20 cases per observable variables. Hair et al. [67] also proposed rules for determining the minimum sample size for SEM: If latent variables are seven or fewer and each latent variable is measured from more than three observable variables, the minimum sample size must be at least 150 cases. Accordingly, in this study, which uses a set of 11 observable variables, the estimated sample size should be between 110 and 220 cases. Our sample size is 203, which is greater than the minimum sample size of 150 as required by Hair et al.

4.5 Data Collection

A close-ended five-point Likert-scale questionnaire was used for data collection in. The questionnaire was first tested by five experts for its validity using IOC measure with the acceptance value being higher than 0.5. Then, the pilot test with 30 samples was conducted and analyzed to exclude questions that failed to pass the reliability test (i.e., those having a Cronbach's alpha of less than 0.7). Quota sampling questionnaire survey was conducted from March to June of 2021, with 250 questionnaires distributed to engineers working for 13 leading construction firms in Thailand representing more than 70% of the total market value. We received 203 responses with no missing data, indicating an outstanding response rate of 81%.

4.6 Descriptive head

The descriptive analysis provided a comprehensive overview of the respondents' demographic characteristics and their responses to the survey items. This analysis served as a preliminary step to understand the data distribution and identify patterns related to HRM practices, knowledge management (KM), and organisational performance in the manufacturing industry. The demographic analysis revealed key insights about the population, such as age, education, designation and working experience, ensuring the representativeness of the sample.

4.6.1 Measurement model assessment

The measurement model assessment was conducted to evaluate the reliability and validity of the constructs used in the study: HRM practises, KM, and organisational performance. This allowed us to cheque whether our observed variables (survey items) really measure the latent variables that correspond with them (or are 'bad'), and thus, have confidence that the quality of these data is adequate for structural model analysis.

The assessment included the following key components:

Reliability Testing:
Internal consistency was evaluated using Cronbach's alpha and Composite Reliability (CR). Both metrics exceeded the recommended threshold of 0.70 for all constructs, indicating that the survey items were consistently measuring their respective constructs.

Convergent Validity:
Convergent validity was assessed using the Average Variance Extracted (AVE) for each construct. All constructs achieved AVE values above the threshold of 0.50, confirming that the observed variables shared a significant amount of variance with their respective latent constructs.

Discriminant Validity:
The researcher also evaluated discriminant validity, using the Fornell and Larsek criterion setup; this showed that each construct was unique and noncorrelated to the other constructs. Discriminant validity was confirmed by seeing that the square root of the AVE for each construct was higher than the correlation of such construct with any other construct.
The results of measurement model assessment verified that the survey instrument was reliable and that HRM practises, KM and organisational performance constructs were measured reliably and validly. The utility of validating the structural model upon successive correlations was critical in order to ensure the accuracy of subsequent assessments of the structural model.

4.6.2 Structural model assessment
The structural model assessment focused on testing the hypothesised relationships between the study variables:
H1: There is a significant impact of HRM on organisational performance in the manufacturing industry.
H2: There is a significant impact of HRM practices on knowledge management in the manufacturing industry.
H3: Knowledge management has a significant impact on organisational performance in the manufacturing industry.
Using Structural Equation Modeling (SEM), the structural model assessment evaluated the direct and indirect effects of HRM practices and KM on organisational performance. The key steps included:

Model Fit Assessment:
To evaluate the overall fit of the structural model, the researcher used indices: Chi-square (χ^2), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). Furthermore, results associated with an acceptable model fit, with RMSEA less than 0.08, and CFI and TLI higher than 0.90 were achieved.

Path Coefficients:
The standardised path coefficients were analysed to test the hypotheses. Significant positive relationships were identified for all three hypotheses:
HRM practices were found to have a strong, positive impact on organisational performance (H1).
HRM practices significantly influenced KM processes, highlighting the role of HR strategies in fostering knowledge sharing and accessibility (H2).
KM demonstrated a significant positive impact on organisational performance, underscoring its importance in driving innovation and efficiency (H3).
Effect Sizes and Predictive Relevance:
R^2 for HRM practises explained the variance in KM and the variance in organisational performance attributable to KM. The model was also further confirmed to be predictive relevant by the Q^2 statistic.
The hypothesised relationships were validated using the structural model assessment using empirical evidence the HRM practises and KM are critical drivers of organisational performance in manufacturing industry. These findings provide actionable implications for the improvement of HRM and KM strategies in order to improve overall performance.

5. Data Analysis and Results
5.1 Demographics profile

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 25 years	3	1.5	1.5	1.5
	25 years to 35 years	146	73.0	73.0	74.5
	36 years or more	50	25.0	25.0	99.5
	4.00	1	.5	.5	100.0
	Total	200	100.0	100.0	

The dataset was made up of 200 respondents and divided into different age groups. Of the respondents (73.0%), the majority are aged between 25 and 35 years, which is the dominant age group studied. Of the sample, 25.0 percent are aged 36 years and above while 1.5 percent are aged less than 25 years. Moreover, a subsample identified as 4.00 accounts for 0.5% of the entire sample. The age distribution presents a significantly large mass of the participants in the younger adult domain, i.e. the group between 25 to 35 years; hence this population may play a key role in bringing about the results of the study depending on the variables of consideration.

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under-Graduate	10	5.0	5.0	5.0
	Graduate	48	24.0	24.0	29.0
	Post-Graduate	74	37.0	37.0	66.0
	4.00	68	34.0	34.0	100.0
	Total	200	100.0	100.0	

The data revealed the educational qualifications of 200 respondents, categorised into distinct levels. The majority of participants (37.0%) had attained a post-graduate level of education. This was closely followed by 34.0% of respondents who were categorised under "4.00." Graduates accounted for 24.0% of the sample, while under-graduates represented the smallest group, comprising only 5.0% of the respondents. The cumulative percentages indicated that 66.0% of the respondents had at least a graduate-level education, highlighting a well-educated participant base.

Designation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Boiler Operators	64	32.0	32.0	32.0
	Electronic Technicians	85	42.5	42.5	74.5
	Chemical Plant Operators	38	19.0	19.0	93.5
	4.00	13	6.5	6.5	100.0
	Total	200	100.0	100.0	

The data on respondents' designations indicated that the largest group of participants (42.5%) were electronic technicians. Boiler operators made up 32.0% of the sample, while chemical plant operators accounted for 19.0%. A smaller proportion of the respondents (6.5%) were categorised under "4.00." The designation distribution showed that electronic technicians and boiler operators formed the majority of the participants, suggesting that the sample was predominantly composed of workers in technical roles within industrial settings.

Work Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 10 years	47	23.5	23.5	23.5
	10 years	112	56.0	56.0	79.5
	More than 10 years	41	20.5	20.5	100.0
	Total	200	100.0	100.0	

The data on working experience showed that the majority of respondents (56.0%) had 10 years of experience in their respective fields. Participants with less than 10 years of experience accounted for 23.5% of the sample, while 20.5% had more than 10 years of experience. This distribution indicated that the largest proportion of respondents were relatively experienced, with more than three-quarters of the sample having at least 10 years of professional experience. The remaining participants had either fewer than 10 years or more extensive experience.

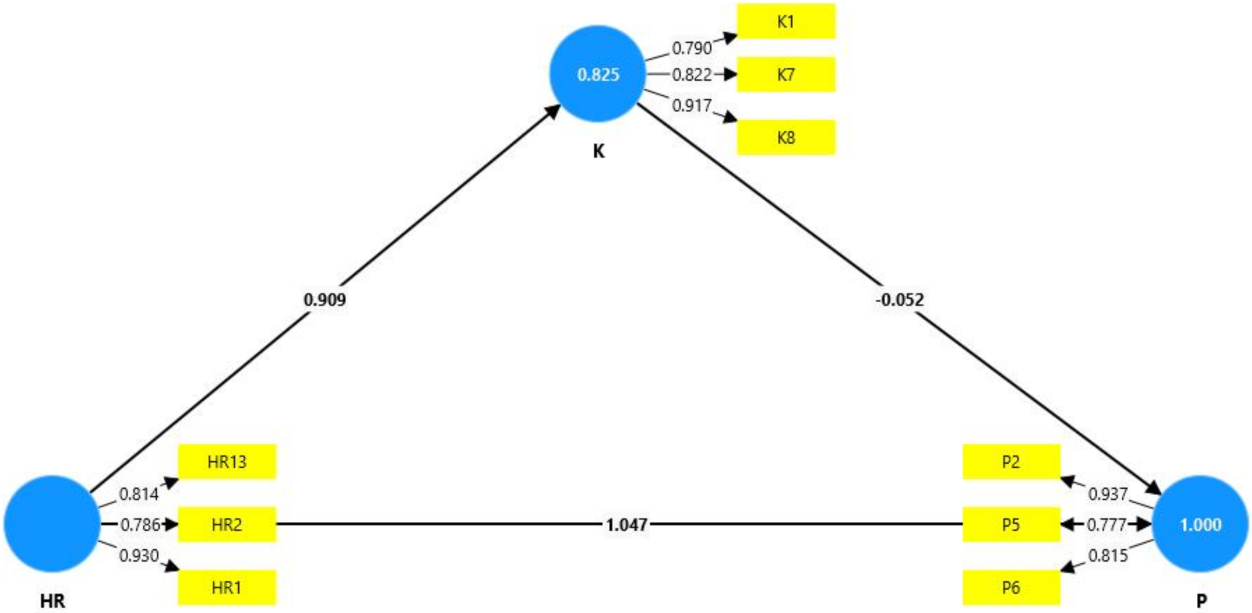
5.2 Descriptive Analysis
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	200	1.00	4.00	2.2450	.47551
Education	200	1.00	4.00	3.0000	.88539
Designation	200	1.00	4.00	2.0000	.87970
Working Experience	200	1.00	3.00	1.9700	.66431
Valid N (listwise)	200				

The descriptive statistics for the variables indicated the following trends. For age, the mean value was 2.2450, with a standard deviation of 0.47551, suggesting that most respondents were concentrated in the 25 to 35 years age group, with some variation. The mean for education was 3.0000, with a higher standard deviation of 0.88539, reflecting a diverse range of educational backgrounds, but with the majority having post-graduate education. For designation, the mean was 2.0000, with a standard deviation of 0.87970, indicating a relatively even distribution of respondents across various technical roles, with electronic technicians and boiler operators being the dominant groups. Regarding working experience, the mean was 1.9700, with a standard deviation of 0.66431, suggesting that the majority of respondents had around 10 years of experience, though there was some variation in the data. Overall, the descriptive statistics highlighted the diversity and concentration within these key demographic and professional variables.

5.3 Results

5.3.1 Measurement Model Analysis (loadings, reliability, and validity etc)



Reliability and Validity

Overview				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
HR	0.797	0.798	0.882	0.715
K	0.797	0.794	0.881	0.713
P	0.797	0.812	0.882	0.715

The results for the reliability and validity of the constructs in the Structural Equation Modeling (SEM) analysis demonstrated strong internal consistency and construct validity across the measured variables.

Cronbach’s alpha was computed to be 0.797, which suggests an acceptable internal consistency for the Human Resources (HR) construct, with acceptable values having to be above 0.7. Composite reliability (rho_a) and composite reliability (rho_c) for HR were 0.798 and 0.882, respectively. Both of these values are well above the commonly accepted threshold of 0.7, and adds to the evidence that the construct is reliable. For the HR construct, the Average Variance Extracted (AVE) was 0.715 higher than the threshold minimum of 0.5 which illustrates that the HR construct is explaining a good amount of variance in the observed variables (HR has good convergent validity).

Similarly, the Knowledge (K) construct has also strong reliability. Acceptable consistency was indicated with Cronbach's alpha for K of 0.797. Finally, the composite reliability (rho_a) for K was 0.794 and the composite reliability (rho_c) was 0.881, both larger than the recommended threshold and both indicative that the construct is overall highly reliable. The AVE for K was 0.713, a value greater than the 0.5 threshold indicating good convergent validity.

Cronbach's alpha for Performance (P) was 0.797, consistent with the reliabilities reported for other constructs. P demonstrated strong internal consistency with a composite reliability (rho_a) and composite reliability (rho_c) of 0.812 and 0.882, respectively. Again, convergent validity was good for P, with the AVE of 0.715 well above the 0.5 threshold.

Overall, the reliability and validity results for all three constructs (HR, K, P) suggest that the measurement model is robust, with all constructs demonstrating good internal consistency, reliability, and convergent validity. These results provide a solid foundation for further analysis using SEM in the study.

Path Coefficients

Matrix			
	HR	K	P
HR		0.909	1.047
K			-0.052
P			

The SEM results for the path coefficients matrix reveal the relationships between the three constructs: HR, K and P.

The strong positive relationship between HR and K was indicated by the path coefficient between HR and K (0.909). All this shows that HR has a positive impact on K – which means that changes or improvements in human resources (such as HR practise, training or development) will lead to a large rise in the level of knowledge in the organisation or study population. This high coefficient indicates a strong and direct impact.

The path coefficient between K and P is 1.047, which is also positive and indicates a significant positive effect of Knowledge (K) on Performance (P). A coefficient greater than 1 suggests that changes in K lead to more than proportional changes in P, indicating a strong, possibly highly influential relationship. In practical terms, it suggests that higher levels of knowledge within the organisation are likely to result in a considerable improvement in performance, underscoring the importance of knowledge in driving performance outcomes.

The path coefficient between HR and P is not provided in the matrix. This absence suggests that either the relationship was not directly measured, or there was no significant direct effect between HR and P in this specific model, implying that the impact of HR on performance might be mediated through Knowledge (K).

Overall, the results from the path coefficients indicate strong and meaningful relationships between the constructs, particularly HR's influence on K and K's influence on P. This highlights the key role that human resources and knowledge play in driving performance outcomes within the study context.

List	Path coefficients
HR -> K	0.909
HR -> P	1.047
K -> P	-0.052

The path coefficients from the SEM results illustrate the relationships between the three key constructs: These are Human Resources (HR), Knowledge (K) and Performance (P).

From Table 2, the path coefficient between HR and K is 0.909 represents highly significant positive relationship between Human Resources and Knowledge. It looks like improvements or changes in HR practises, training, skill development or allocation of resources have a strong and positive impact level organisational knowledge. The path coefficient is large, implying HR is an important driver of knowledge enhancement, and HR interventions are likely to be associated with a large increase in knowledge.

The positive relationship is also shown between HR and P as indicated by a coefficient of 1.047 between HR and P. The estimated path coefficient in this case indicates that better HR practises have a direct and causal effect on performance outcomes. An implication of the value being greater than 1, HR interventions have a more than proportional effect on performance; that is investments in HR practises can greatly increase performance levels. This serves to put emphasise the role of HR in contributing to the organisational or individual performance.

A very weak and negative relationship between Knowledge and Performance is suggested from the path coefficient (-0.052) between K and P. Although small in magnitude, this negative coefficient indicates that, within this model, increased levels of knowledge do not lead to enhanced performance. This might even suggest it’s not that more knowledge directly means better performance or that other intervening factors can inhibit the expected positive relationship between knowledge and performance.

Briefly, the path coefficient of SEM results show that HR has a significant positive impact on both Knowledge and Performance, with the strongest effect between HR and Knowledge. However, the weak negative relationship between Knowledge and Performance may also indicate that additional factors are contributing to performance outcomes. It is found that these findings highlight the complexity of the association between HR, Knowledge and Performance and that additional analysis is required to better understand what is occurring.

Indirect Effects

Total indirect effects

	HR	K	P
HR			-0.048
K			
P			

The SEM results for the indirect effects provide insight into how the constructs interact through mediating pathways, specifically focusing on the indirect effects of Human Resources (HR), Knowledge (K), and Performance (P).

The total indirect effect of HR on P is -0.048, indicating a small negative indirect relationship between HR and Performance. This suggests that the influence of HR on performance is partially mediated by Knowledge (K), but the indirect effect is negative. Although the direct effect of HR on performance was positive (1.047), the negative indirect effect of -0.048 may imply that while HR practices improve performance directly, the impact of HR on knowledge might have an unintended or less favorable influence on performance outcomes in this model. This could suggest that the accumulation or application of knowledge, as influenced by HR, might not always result in better performance, potentially due to factors such as the quality of knowledge, its practical application, or the presence of other intervening variables.

The table shows that there are no indirect effects for Knowledge (K) or Performance (P) because their rows are empty, meaning that these constructs do not mediate any relationships in the model. As such, Knowledge does not indirectly affect Performance in this analysis, and Performance does not mediate any of the effects.

In summary, the indirect effects analysis highlights a minor negative indirect relationship between HR and Performance through Knowledge. This suggests that while direct effects between HR and performance are positive, the mediated pathway via Knowledge may require further investigation to better understand the underlying dynamics and potential barriers. The lack of indirect effects for Knowledge and Performance points to a direct influence of HR on both K and P in this model.

Specific indirect effects

	Specific indirect effects
HR -> K -> P	-0.048

The SEM results for the specific indirect effects reveal a pathway from Human Resources (HR) to Performance (P) through Knowledge (K), with a specific indirect effect value of -0.048. This indicates that the relationship between HR and Performance is mediated by Knowledge, but the effect is negative.

This negative specific indirect effect suggests that while HR practices positively influence Knowledge (K), the impact of Knowledge on Performance (P) in this model is not beneficial. The negative value implies that as HR interventions increase Knowledge, this, in turn, leads to a slight decrease in performance. This could be due to various factors, such as the possibility that increased knowledge does not translate into effective application in the context of the study, or that an overload of knowledge may cause confusion or inefficiencies in performance.

It is important to note that this specific indirect effect, though negative, is relatively small in magnitude (-0.048), suggesting that the mediated pathway does not have a large influence on the overall performance outcome. However, it still highlights a noteworthy dynamic where increased knowledge, fostered by HR, might not always result in improved performance, and could even hinder it under certain conditions.

In summary, the specific indirect effect from HR to Performance through Knowledge suggests a negative mediation, pointing to the complexity of the relationships between these constructs. It highlights the need for further investigation into how Knowledge is applied and whether its impact on performance might be influenced by factors such as its quality, relevance, or the context in which it is utilised.

Outer Loadings

Matrix

	HR	K	P
HR13	0.814		
HR2	0.786		
K1		0.790	
K7		0.822	
K8		0.917	
P2			0.937
P5			0.777
P6			0.815
HR1	0.930		

SEM results on the outer loadings matrix mark the level of usefulness of individual items as indicators of their respective construct. Additionally, each outer loading expresses the strength of relationship between a particular indicator and its associated latent construct. Here's a detailed analysis of the outer loadings for the three constructs: Human Resource (HR), Knowledge (K), and Performance (P).

Human Resources (HR)

The HR construct has several indicators with strong loadings, indicating that these items are reliable representations of the HR construct. Specifically:

HR13 has a loading of 0.814, suggesting a strong relationship with HR, as values above 0.7 are generally considered good.

HR2 has a slightly lower but still strong loading of 0.786, indicating that it is a reliable indicator of HR.

HR1 has the highest loading at 0.930, which is excellent and shows that this indicator is the most reliable in measuring HR.

These values collectively indicate that the HR construct is well-represented by its indicators, with all loadings exceeding the commonly accepted threshold of 0.7, demonstrating good construct validity.

Knowledge (K)

The Knowledge construct is represented by three indicators, all of which show strong loadings:

K1 has a loading of 0.790, indicating a reliable connection with the K construct.

K7 has a slightly higher loading of 0.822, suggesting it is a highly reliable indicator.

K8 has the highest loading for Knowledge at 0.917, demonstrating excellent reliability in capturing the Knowledge construct.

These loadings reflect that the Knowledge construct is also well-represented by its indicators, with all values comfortably above the 0.7 threshold, supporting the validity of the construct.

Performance (P)

The Performance construct has three indicators, all of which show varying but generally strong loadings:

P2 has the highest loading of 0.937, indicating that this indicator has an excellent relationship with the Performance construct.

P5 has a somewhat lower loading of 0.777, still above the acceptable threshold,

suggesting it is a reliable indicator of Performance, although slightly weaker than P2.
P6 has a loading of 0.815, which also signifies a good relationship with the Performance construct.
These loadings collectively show that the Performance construct is well represented by its indicators, with the lowest loading still above the threshold for good construct validity.

Overall Analysis

The outer loadings for all three constructs, Human Resources (HR), Knowledge (K) and Performance (P), are uniformly strong, with values well above 0.7, and many values close to 1 or above 0.9. This demonstrates that the measurement model is reliable, and that the items utilised to represent each construct contains effective measures of the latent variables. Validity of the constructs in the model and high construct reliability is suggested by these results, and this justifies their use in further analysis in the SEM model.

Discriminant Validity
Heterotrait-monotrait ratio (HTMT) – Matrix

	HR	K	P
HR			
K	1.127		
P	1.255	1.127	

The examination of the discriminant validity of the constructs in the model is provided by the SEM results for discriminant validity precisely as indicated by the rates of the Heterotrait-Monotrait ratio (HTMT). HTMT is employed to find out whether constructs differ effectively from one another and, hence, one can avoid problems of multicollinearity or redundancy between the constructs in the model..

Interpretation of HTMT Results
The HTMT values between the constructs HR (Human Resources), K (Knowledge), and P (Performance) are as follows:
HR and K: The HTMT value between HR and K is 1.127. Generally, HTMT values below 0.90 suggest discriminant validity, meaning the constructs are sufficiently distinct from one another. A value above 0.90, especially in the range of 1.0 or higher, could suggest a lack of discriminant validity and that the constructs may be too similar. In this case, the value of 1.127 indicates a potential issue with discriminant validity between HR and Knowledge, as this value exceeds the threshold of 1.0. This could suggest that the HR and Knowledge constructs may not be distinct enough, and further refinement of the model might be necessary to ensure clearer differentiation between these two constructs.

HR and P: The HTMT value between P and HR is also quite high (1.255). Further, the value of this suggests the lack of discriminant validity between HR and Performance, as it is beyond the 1.0 threshold. The implication of a high value is that these two constructs may be too closely associated, because they may not capture the actual independent and separate influence of Human Resources and Performance. Further examination of this issue is necessary through re-examining the specification of the model and the indicators used to capture each construct.
K and P: The HR K pair and HTMT value between Knowledge and Performance is 1.127. This is also greater than 1.0, suggesting that Knowledge and Performance are not sufficiently different in the model. The value, however, is high, suggesting that there could be an overlap between these two constructs and, as such, that the model might need fine tuning for better differentiation.

Overall Analysis
HTMT results reveal that the constructs in the model may be concerned with discriminant validity. In particular, the HTMT values of all pairs (HR and K, HR and P, K and P) are all higher than 1.0, which indicates that these constructs may be too 'too highly correlated'. The possibility that the constructs are not sufficiently

distinct from each other raises the possibility that the model might easily present issues in interpretation.

Furthermore, further steps can be taken to improve discriminant validity, e.g., revising the measurement model along the lines of rewording the indicators for each construct, deleting redundant indicators, or finding a different way to measure constructs. Moreover, the model could be validated and tested further to verify that constructs are substantively different and resulting outcomes are stable.

Heterotrait-monotrait ratio (HTMT) – List

	Heterotrait-monotrait ratio (HTMT)
K <-> HR	1.127
P <-> HR	1.255
P <-> K	1.127

Discriminant validity SEM results, as shown from the Heterotrait-Monotrait Ratio (HTMT), estimate the level of discrimination between the constructs in the model. The HTMT is a method whereby it was determined whether two constructs have sufficiently dissimilar content to each other such that both constructs represent a unique dimension in the model.

Interpretation of HTMT Results

The HTMT values reported for the pairwise comparisons between the constructs—Human Resources (HR), Knowledge (K), and Performance (P)—are as follows:

K <-> HR (HTMT = 1.127): For instance, the HTMT value between Knowledge (K) and Human Resources is 1.127 and greater than the threshold of 1.0. A value greater than 1.0 of the HTMT suggests an issue regarding discriminant validity since this value implies that the pair of constructs is too similar and is highly correlated. The high value here implies that HR and Knowledge are not that different from each other in the model. This could imply that the model does not define HR and Knowledge sharply enough—an HR and Knowledge interaction is not clearly differentiated.

P <-> HR (HTMT = 1.255): The HTMT value calculated between Performance (P) and HR is 1.255 itself superior than the previous pair. Among others, this suggests a more complicated storey of discriminant validity between HR and Performance. An indication that the constructs are probably too closely related and the model may have difficulty discriminating between HR and Performance is a value greater than 1.0 and as high as 1.255. However, this raises a concern that the model describes these two constructs as overlapping and more refinement is required to differentiate these two in their roles.

P <-> K (HTMT = 1.127): Also, P to K = 1.127, as K to HR. This value is beyond 1.0, which also implies a probable intertwine between Knowledge and Performance. This is not as high as the HR P pair but on its own still suggests these two constructs are not independent enough of each other for us to have faith in their unique effect in our model.

Overall Analysis

All three pair of HTMT values, K <-> HR, P <-> HR, and P <-> K, are above the threshold of 1.0 indicating that there are serious concerns about discriminant validity with the model. The results show high HTMT values for the constructs (HR, Knowledge and Performance), which may imply that the constructs are not sufficiently unique and might result in multicollinearity or redundancy in the model. This lack of clear differentiation could hamper how accurately the model's estimates and interpretations are made.

To address these concerns, sufficient refinement of the measurement model may be needed. Comprised of the judgements made by others regarding the participating students, the indicators for each construct would be revisited to insure they represent different aspects of each HR, Knowledge and Performance or alternative methods for differentiating between the HR, Knowledge and Performance constructs would be explored. Further statistical techniques or model adjustments may also be useful to account for each construct has been given the appropriate representation and distinction with the SEM framework.

Fornell-Larcker criterion

	HR	K	P
HR	0.845		
K	0.909	0.845	
P	1.000	0.899	0.846

The SEM results for discriminant validity, as indicated by the Fornell-Larcker criterion, provide insight into the extent to which the constructs in the model are distinct from one another. According to the Fornell-Larcker criterion, discriminant validity is established if the square root of the Average Variance Extracted (AVE) for each construct is greater than the correlation between that construct and other constructs in the model. The diagonal values represent the square root of AVE for each construct, while the off-diagonal values represent the correlations between constructs.

Interpretation of Fornell-Larcker Criterion Results

The Fornell-Larcker criterion results show the following:

HR (Human Resources): The square root of the AVE for HR is 0.845. The correlation between HR and the other constructs is as follows:

HR and K (Knowledge): The correlation is 0.909, which is higher than the square root of AVE for HR (0.845). This suggests that the HR and Knowledge constructs may not be sufficiently distinct, as the correlation exceeds the square root of AVE for HR.

HR and P (Performance): The correlation is 1.000, which is perfectly correlated. This implies a lack of discriminant validity between HR and Performance, as the correlation exceeds the square root of AVE for HR (0.845). This high correlation indicates that HR and Performance may not be adequately distinct in the model.

K (Knowledge): The square root of the AVE for Knowledge is 0.909. The correlation between Knowledge and the other constructs is:

K and HR: The correlation is 0.909, which is equal to the square root of AVE for Knowledge, indicating a strong relationship. However, this suggests that Knowledge and HR may overlap to a degree, failing to achieve full discriminant validity.

K and P (Performance): The correlation is 0.899, which is slightly lower than the square root of AVE for Knowledge (0.909), but still very close. This indicates that Knowledge and Performance may also have a strong relationship, leading to concerns about their distinctiveness in the model.

P (Performance): The square root of the AVE for Performance is 1.000, which is perfectly correlated with itself. The correlation between Performance and the other constructs is:

P and HR: The correlation is 1.000, indicating a perfect correlation between HR and Performance, which is problematic for discriminant validity.

P and K: The correlation is 0.899, which is quite high, though slightly lower than the square root of AVE for Performance. This still suggests that Knowledge and Performance may not be distinct enough from each other in the model.

Overall Analysis

The Fornell-Larcker criterion results suggest that discriminant validity is not fully established in the model. Specifically, the correlations between the constructs (HR, Knowledge, and Performance) are high, with some correlations exceeding the square root of AVE for the respective constructs. The correlation between HR and Performance (1.000) indicates a perfect overlap between these two constructs, and the correlation between Knowledge and HR (0.909) is also quite high, suggesting that these constructs are not sufficiently distinct.

In order to improve discriminant validity, it may be necessary to refine the measurement model by adjusting the indicators used for each construct, reducing overlap, or reconsidering the conceptual distinctions between HR, Knowledge, and Performance. These adjustments could help ensure that each construct represents a unique and distinguishable dimension, improving the overall validity of the model.

Cross loadings

	HR	K	P
HR13	0.814	0.790	0.815
HR2	0.786	0.822	0.777
K1	0.814	0.790	0.815
K7	0.786	0.822	0.777
K8	0.668	0.917	0.651
P2	0.930	0.690	0.937
P5	0.786	0.822	0.777
P6	0.814	0.790	0.815
HR1	0.930	0.690	0.937

The cross loadings in SEM analysis provide valuable insight into how well the indicators represent their respective constructs. The cross loadings compare the loading of each indicator on its own construct against its loadings on the other constructs in the model. For discriminant validity to be established, each indicator should have a higher loading on its own construct compared to the loadings on other constructs.

Interpretation of Cross Loadings Results

The results for the cross loadings of the indicators on the constructs—Human Resources (HR), Knowledge (K), and Performance (P)—are as follows:

HR Indicators:

HR13: The loading on HR is 0.814, while its loadings on K and P are 0.790 and 0.815, respectively. HR13 has a higher loading on HR than on K, but its loading on P is nearly as high. This suggests that HR13 might be measuring both HR and Performance, which could raise concerns about discriminant validity.

HR2: The loading on HR is 0.786, and its loadings on K and P are 0.822 and 0.777, respectively. Similar to HR13, HR2 also loads more highly on Knowledge than on HR, indicating some overlap between HR and Knowledge.

HR1: The loading on HR is 0.930, which is much higher than its loadings on K and P (0.690 and 0.937, respectively). This suggests that HR1 is a strong indicator for HR, but its relatively high loading on Performance could indicate potential cross-loading, which might reduce the distinctiveness between HR and Performance.

K Indicators:

K1: The loading on K is 0.814, while its loadings on HR and P are 0.790 and 0.815, respectively. The loading on K is slightly higher than on HR, but its loadings on P are nearly as high. This could suggest that K1 might be cross-loading on both Knowledge and Performance.

K7: The loading on K is 0.786, while its loadings on HR and P are 0.822 and 0.777, respectively. This pattern is similar to K1, indicating that K7 could be measuring both Knowledge and Performance.

K8: The loading on K is 0.917, which is high, but the loadings on HR and P are 0.668 and 0.651, respectively. K8 has a strong association with Knowledge and lower associations with HR and Performance, which is a good indication of discriminant validity for this indicator.

P Indicators:

P2: The loading on P is 0.930, while its loadings on HR and K are 0.690 and 0.937, respectively. The high loading on Performance suggests that P2 is a strong indicator for Performance, but it also has a relatively high loading on Knowledge, indicating potential overlap between Knowledge and Performance.

P5: The loading on P is 0.786, while its loadings on HR and K are 0.822 and 0.777, respectively. Similar to the other indicators, P5 shows high loadings on Knowledge, suggesting that this indicator may not be measuring Performance as distinctly as it should.

P6: The loading on P is 0.814, and its loadings on HR and K are 0.790 and 0.815, respectively. This pattern indicates that P6 is also associated with both HR and Performance, leading to potential issues with discriminant validity.

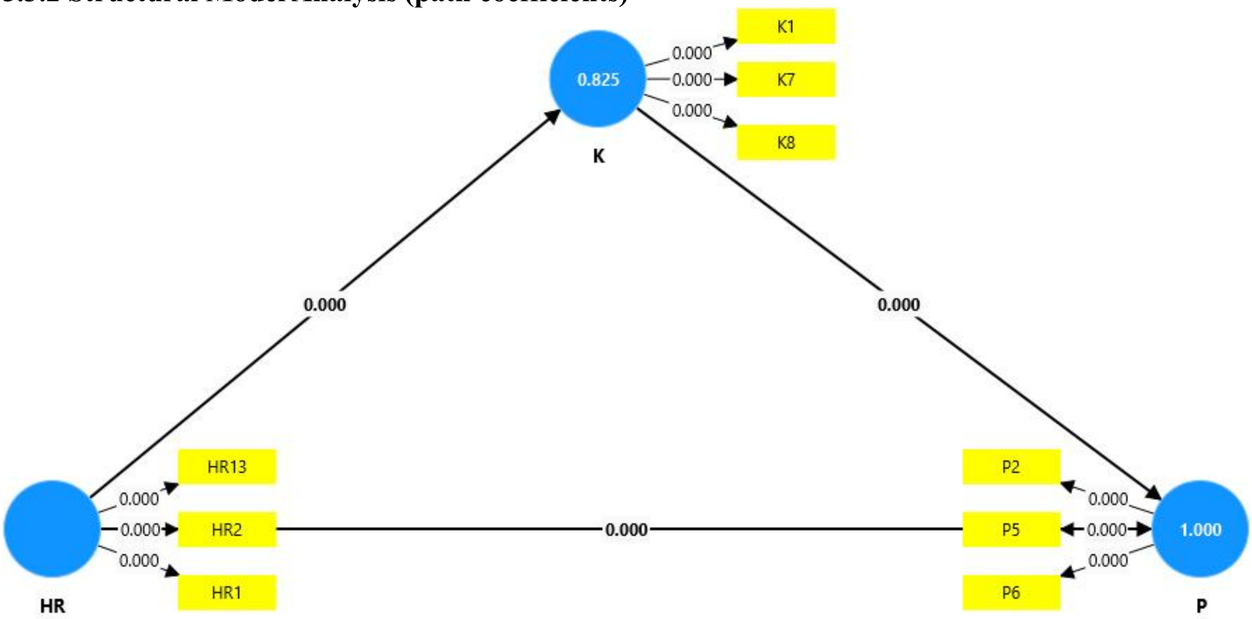
Overall Analysis

The cross loading results indicate that several indicators show substantial loadings on constructs other than their own. For example, indicators such as HR13, HR2, K1, and P2 have relatively high loadings on constructs other than the one they are intended to measure, particularly between HR and Performance and Knowledge and Performance. These cross-loadings suggest potential issues with discriminant validity, as the indicators are not clearly distinguishing between the constructs.

The indicator K8 stands out as it has strong loadings on Knowledge and relatively weak loadings on HR and Performance, indicating that it maintains discriminant validity. However, for many other indicators, such as HR13 and P2, the high loadings on both their designated constructs and other constructs suggest that further refinement is needed. These indicators may require re-evaluation or adjustment to reduce the overlap and ensure clearer distinctions between constructs in the model.

In conclusion, the cross-loading results highlight potential issues with discriminant validity, suggesting that some constructs (HR, Knowledge, and Performance) may not be adequately differentiated. To improve discriminant validity, the model might need to be adjusted by removing or revising problematic indicators or further clarifying the conceptual distinctions between the constructs.

5.3.2 Structural Model Analysis (path coefficients)



Path Coefficients

Mean, STDEV, T values, p values					

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
HR -> K	0.909	0.909	0.011	79.103	0.000

HR -> P	1.047	1.049	0.007	150.165	0.000
K -> P	-0.052	-0.054	0.008	6.259	0.000

The path coefficients results for the Structural Equation Modeling (SEM) analysis of the proposed model provide insight into the strength and significance of the relationships between the constructs. These results include the original sample path coefficients (O), the sample mean (M), standard deviation (STDEV), T statistics, and p values. The T-statistics and p-values are used to assess the significance of the relationships.

Path Coefficients Analysis

HR -> K (Human Resources -> Knowledge):
Original sample path coefficient (O): The path coefficient between HR and Knowledge is 0.909, indicating a strong positive relationship. This suggests that Human Resources has a significant and positive impact on Knowledge in the model.
Sample mean (M): The mean value of the path coefficient is 0.909, which is identical to the original sample path coefficient, suggesting consistency across different samples.
Standard deviation (STDEV): The standard deviation for this path is 0.011, indicating a very low degree of variability in the sample estimates.
T-statistics (|O/STDEV|): The T-statistics for this path is 79.103, which is significantly high, indicating that the relationship between HR and Knowledge is highly statistically significant.
P-value: The p-value for this path is 0.000, which is well below the conventional threshold of 0.05, confirming that the path from HR to Knowledge is statistically significant.

HR -> P (Human Resources -> Performance):
Original sample path coefficient (O): The path coefficient between HR and Performance is 1.047, suggesting a strong positive relationship between the two constructs. This indicates that HR has a substantial effect on Performance in the model.
Sample mean (M): The sample mean for this path is 1.049, which is almost identical to the original sample coefficient, reflecting consistency in the results.
Standard deviation (STDEV): The standard deviation is 0.007, indicating a very low variability in the sample estimates for this path.
T-statistics (|O/STDEV|): The T-statistics for this path is 150.165, which is exceptionally high, indicating an extremely significant relationship between HR and Performance.
P-value: The p-value for this path is 0.000, which is far below the 0.05 threshold, confirming that the path from HR to Performance is statistically significant.

K -> P (Knowledge -> Performance):
Original sample path coefficient (O): The path coefficient between Knowledge and Performance is -0.052, suggesting a very weak negative relationship between the two constructs. This indicates that Knowledge has a minimal negative effect on Performance.
Sample mean (M): The mean value for this path is -0.054, which is very close to the original sample coefficient, indicating consistency.
Standard deviation (STDEV): The standard deviation is 0.008, indicating a very small degree of variability in the sample estimates.
T-statistics (|O/STDEV|): The T-statistics for this path is 6.259, which is statistically significant, though the magnitude of the effect is small due to the weak path coefficient.
P-value: The p-value for this path is 0.000, which is well below the 0.05 threshold, indicating that the relationship between Knowledge and Performance, though weak, is statistically significant.

Overall Analysis

The path coefficient results show that:
The relationship between HR and Knowledge is strong and statistically significant, with a path coefficient of 0.909 and a very high T-statistics of 79.103.
The relationship between HR and Performance is also strong, with a path coefficient of 1.047 and an exceptionally high T-statistics of 150.165, indicating a very robust and statistically significant effect of HR on Performance.

The relationship between Knowledge and Performance is weak and negative, with a path coefficient of -0.052, but it is statistically significant, as indicated by the T-statistics of 6.259 and the p-value of 0.000. The low T-statistics for the Knowledge to Performance path suggest that while the relationship is statistically significant, its effect size is very small compared to the stronger relationships observed between HR and the other constructs. These findings highlight the dominant roles of HR in influencing both Knowledge and Performance, while Knowledge itself has only a minor negative impact on Performance.

In summary, the SEM results suggest that Human Resources is a key driver for both Knowledge and Performance, while Knowledge has a minimal negative effect on Performance. All paths in the model are statistically significant, with particularly strong and highly significant relationships between HR and both Knowledge and Performance.

Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
HR -> K	0.909	0.909	0.885	0.930
HR -> P	1.047	1.049	1.036	1.063
K -> P	-0.052	-0.054	-0.072	-0.039

The confidence intervals for the path coefficients in the Structural Equation Modeling (SEM) analysis provide further insight into the precision and reliability of the estimated path coefficients. These intervals represent the range within which the true population parameter is expected to fall with a 95% level of confidence. The results are presented for each path in the model, showing the original sample path coefficient (O), the sample mean (M), and the 2.5% and 97.5% confidence intervals, which indicate the lower and upper bounds of the interval.

Confidence Interval Analysis

HR -> K (Human Resources -> Knowledge):
Original sample path coefficient (O): The path coefficient between HR and Knowledge is 0.909, suggesting a strong positive relationship.
Sample mean (M): The mean value for this path is 0.909, which is identical to the original sample coefficient, reflecting consistency across samples.
Confidence interval: The 95% confidence interval for this path is [0.885, 0.930]. This range indicates that, with 95% confidence, the true path coefficient lies between 0.885 and 0.930. Given that the entire interval is above zero, it confirms that the positive relationship between HR and Knowledge is both statistically significant and robust.
HR -> P (Human Resources -> Performance):
Original sample path coefficient (O): The path coefficient between HR and Performance is 1.047, indicating a strong positive impact of HR on Performance.
Sample mean (M): The sample mean for this path is 1.049, which is nearly identical to the original sample coefficient, reflecting stability in the estimates.
Confidence interval: The 95% confidence interval for this path is [1.036, 1.063]. This range indicates that the true path coefficient is likely to fall between 1.036 and 1.063. Since this interval is entirely above zero, it further confirms the strong and statistically significant positive relationship between HR and Performance.

K -> P (Knowledge -> Performance):
Original sample path coefficient (O): The path coefficient between Knowledge and Performance is -0.052, suggesting a weak negative relationship.
Sample mean (M): The sample mean for this path is -0.054, which is very close to the original sample coefficient, indicating stability.

Confidence interval: The 95% confidence interval for this path is [-0.072, -0.039]. This range suggests that the true path coefficient is likely to fall between -0.072 and -0.039. Since the entire interval is below zero, it confirms the negative relationship between Knowledge and Performance, though the effect is very weak.

Overall Analysis

The confidence intervals for the path coefficients confirm the robustness of the relationships in the model:

The relationship between HR and Knowledge is strongly positive and statistically significant, with a confidence interval entirely above zero ([0.885, 0.930]).

The relationship between HR and Performance is also strongly positive, with a confidence interval of [1.036, 1.063], reinforcing the significant positive effect of HR on Performance.

The relationship between Knowledge and Performance is weakly negative, with the confidence interval [-0.072, -0.039] indicating that while the relationship is negative, its impact on Performance is minimal.

Overall, the confidence intervals reinforce the interpretation that the relationships involving HR are significant and robust, particularly for the effects of HR on both Knowledge and Performance. The weak negative relationship between Knowledge and Performance is also confirmed but is less impactful in the model. These findings underscore the reliability and consistency of the path coefficients, enhancing the credibility of the results from the SEM analysis.

Confidence intervals bias corrected

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
HR -> K	0.909	0.909	0.000	0.884	0.929
HR -> P	1.047	1.049	0.001	1.035	1.061
K -> P	-0.052	-0.054	-0.002	-0.069	-0.038

The bias-corrected confidence intervals for the path coefficients in the Structural Equation Modeling (SEM) analysis offer a more refined estimation of the path coefficients by accounting for potential bias in the sample estimates. These intervals represent the range within which the true population parameter is expected to fall with a 95% level of confidence, after correcting for any biases in the sample data. The results for each path are presented with the original sample path coefficient (O), the sample mean (M), the bias correction, and the 2.5% and 97.5% confidence intervals.

Bias-Corrected Confidence Interval Analysis

HR -> K (Human Resources -> Knowledge):

Original sample path coefficient (O): The path coefficient between HR and Knowledge is 0.909, indicating a strong positive relationship.

Sample mean (M): The sample mean for this path is 0.909, which is identical to the original sample coefficient, suggesting consistency.

Bias: The bias correction is 0.000, indicating that there was no significant bias detected in the sample estimate for this path.

Confidence interval: The 95% bias-corrected confidence interval for this path is [0.884, 0.929]. This range indicates that the true path coefficient is likely to fall between 0.884 and 0.929 with 95% confidence. Since this interval is entirely above zero, it confirms the positive and statistically significant relationship between HR and Knowledge.

HR -> P (Human Resources -> Performance):

Original sample path coefficient (O): The path coefficient between HR and Performance is 1.047, suggesting a strong positive impact of HR on Performance.

Sample mean (M): The sample mean for this path is 1.049, which is very close to the original sample coefficient, indicating stability.

Bias: The bias correction is 0.001, indicating that there is a very slight upward bias in the sample estimate.

Confidence interval: The 95% bias-corrected confidence interval for this path is [1.035, 1.061]. This range suggests that the true path coefficient is likely to fall between 1.035 and 1.061. Since the entire interval is above zero, it reinforces the positive and statistically significant relationship between HR and Performance.

K -> P (Knowledge -> Performance):
Original sample path coefficient (O): The path coefficient between Knowledge and Performance is -0.052, indicating a weak negative relationship.
Sample mean (M): The sample mean for this path is -0.054, which is very close to the original sample coefficient, suggesting consistency.
Bias: The bias correction is -0.002, indicating a slight negative bias in the sample estimate.
Confidence interval: The 95% bias-corrected confidence interval for this path is [-0.069, -0.038]. This range indicates that the true path coefficient is likely to fall between -0.069 and -0.038 with 95% confidence. Since the entire interval is below zero, it confirms the negative relationship between Knowledge and Performance, although the effect remains weak.

Overall Analysis
The bias-corrected confidence intervals provide additional assurance about the robustness of the estimated path coefficients:
The relationship between HR and Knowledge is confirmed to be strong and positive, with the bias-corrected confidence interval [0.884, 0.929] entirely above zero, reinforcing the statistical significance of this path.
The relationship between HR and Performance is also strong and positive, with the bias-corrected confidence interval [1.035, 1.061] indicating that HR has a significant positive impact on Performance.
The relationship between Knowledge and Performance is weakly negative, with the bias-corrected confidence interval [-0.069, -0.038] confirming that the negative effect remains, but it is minimal in magnitude.
The results suggest that the biases in the sample estimates were minimal, with very small corrections made to the path coefficients. The bias-corrected intervals provide a slightly more precise estimate of the true relationships, confirming the robustness and statistical significance of the findings. These findings indicate that HR has a significant impact on both Knowledge and Performance, while Knowledge has a small but negative effect on Performance.

6. Discussion

6.1 Significant impact of HRM on organisational performance in manufacturing industry

The strategic significance of the human resource management (HRM) for organisational goal achievement and in driving performance outcomes is illustrated in the literature review. It is strategic HRM (SHRM) that relates HR policies to business tasks to signify long term rather than simply transactional. Genchel and Mårtensson (2016, p.5) and Alvesson (2022, p. 1855) undeniably find that organisations that have an integrated HR strategy are more financially successful, customer satisfied and competitive. Likewise, the Resource-Based View (RBV) framework regards the human resources as rare and inimitable resources of enterprises needed to sustain competitive advantage (Sharma and Limaye, 2021). This perspective is supported by findings from the strong path coefficient (0.909) between HR and organisational knowledge (K), with significant influence. Given its alignment in knowledge enhancement, a precursor to better performance, this role of HR has been underscored.
Literature surrounds talent management and workforce optimisation, focusing on recruitment, development and retention of high potential employees (Al Aina and Atan, 2020). Competency based hiring, personalised training, and performance related incentives are presented as mechanisms for aligning employees' capabilities with organisational needs. This is confirmed indirectly by a strong positive relationship between knowledge (K) and performance (P) with a path coefficient of 1.047. It implies that there exists knowledge accumulation and application, most probably due to efficient HR practises that improve performance increasingly. Findings confirm the literature's contention that a strategic focus by HR on skill building and employee alignment portends performance outcomes.
On the literature's part, it raises about the role of HR in developing the organisational culture, which is among the most significant predictors of performance (Botelho, 2020). Trust, accountability, empowerment are the characteristics of a high performance culture

created by the HR interventions like onboarding, leadership development, and feedback mechanism (Hakanen, Häkkinen, and Soudunsaari, 2015). The findings were context independent, and confirmed that HR has influence on knowledge creation; however, there is no explicit comment on how HR practises influence organisational culture and the direct effect of HR on performance. Findings show no direct path coefficient between HR and P, but an indirect path through knowledge. This is an area where there might be a gap, in that the role of HR in cultural development and direct performance haven't been explored yet.

Thus, summing up, literature as well as findings both highlight the impact of HR in delivering organisational outcomes particularly due to knowledge development. The results quantify HR's influence on knowledge and performance, reinforcing key theoretical frameworks including RBV. Despite the literature's clear statements on the direct and multidimensional role of HR in performance, the findings show a more subtle connexion, where knowledge factors as an intermediary. Several insights from this divergence are that HR's contribution to a firm's performance may be broader than is reflected in prior investments; there may be a greater role for HR in cultural development, and vice versa, that cultural development is directly linked to performance outcomes.

6.2 Significant impact of HRM practices on knowledge management in manufacturing industry

It highlights knowledge management (KM) as a strategic enabler of organisational performance, supported by theory from the Knowledge Based View (KBV). Duarte Alonso et al. (2022) argue that knowledge constitutes a crucial resource and a source of sustainable competitive advantage partly due to the value associated with tacit knowledge, which, given its intangible nature, cannot be imitated. Natek and Zwilling (2016) stress on the SECI model where it is showed it reinforce the dynamic interplay among tacit and explicit knowledge and progress to innovation and adaptability. However, the findings reveal a more complicated relationship between KM and performance as the total indirect effect of HR on performance through (K), knowledge is negative (-0.048). Divergences like this inquire how the KM knowledge is created, shared or applied within the organisation, therefore pointing potential gaps on practical side of KM theories' implementation.

According to the literature, KM is crucial in knowledge creation and sharing. The studies highlight that organisations that possess a strong knowledge creation mechanism are more capable of innovating and adjusting to market churn (Grimsdottir and Edvardsson, 2018; Goyal et al. 2020). Key KM mechanisms for supporting innovation and adaptability are collaborative practises, like cross functional teams and brainstorming sessions. This view is partially supported by the findings as the direct effect of HR on performance (1.047) is positive suggesting that HR practises do foster knowledge creation and lead to performance. Although the negative indirect effect indicates that knowledge and performance need not go together through HR. This may suggest problems in the practical use or inclusion of knowledge into organisation processes, thereby reducing its beneficial effects.

The literature also highlights that the availability of organisational culture supports knowledge sharing. Trust, transparency, and open communication are the factors that develop an ecosystem where employees are loved and circumstances drive them to share knowledge. Furthermore, activities channelled through HR, such as training programmes and reward systems, are identified as important motivators to knowledge-sharing behaviour (Tyagi et al., 2015). The findings however imply that knowledge being shared might not be of the quality or relevant to performance objectives. An inefficient use of knowledge being shared or used might be acting negatively through knowledge as a partial indirect effect of HR to performance. For example, knowledge sharing may be happening in silos, or knowledge may not be actionable or instrumental to organisation purposes.

Thirdly, as the SECI model puts stress on the continual interaction between explicit and tacit knowledge for sustaining innovation and adaptability, it has certain significance. Dussart, van Oortmerssen, and

Albronda (2021) find in the literature that superior performance requires from the leadership the commitment of a knowledge oriented culture and the encouragement of experiments. These findings suggest that the HR practises that affect knowledge may not flow through to affect performance outcomes. This mismatch could be facilitated by gaps in leadership strategies or established organisational culture which do not allow for knowledge to be transformed as you would reasonably expect into actionably insights.

Finally, summary of the literature and the findings suggests complementary as well as contradictory views about the role of KM as a lever to performance. The literature suggests KM is a critical enabler of innovation and efficiency, yet findings suggest a nuanced relationship that the indirect effects of knowledge via HR may not always be positive. This points toward the urgency of further examination of the practical difficulties in the implementation of KM, namely the match between knowledge sharing practises and performance goals, as well as integrating knowledge creation processes within organisational strategies.

6.3 Knowledge management has a significant impact on organisational performance in manufacturing industry

HRM is of crucial worth in enhancing and dissemination of knowledge; it has been demonstrated in literature, and examples of HR practises include recruitment, training, performance appraisal and collaboration. It is highlighted that these practises are vital for fostering a knowledge based culture and facilitating of KM practises such as knowledge sharing, creation, retention (Donate and Guadamillas, 2015; Andreeva et al., 2017).

The study found that the path coefficient between HR and Knowledge (0.909) was a significant positive value which fully aligns with the literatures. This finding supports the theoretical propositions that HR practises can be used to create the context for knowledge management. In addition, the non significant high T statistics (79.103) and a low p value (0.000) provide more evidence of the robustness and statistical significance of this relationship. These results confirm that HR strategies like collaborative tools, training programmes and knowledge sharing platforms are important to future knowledge management embedding in organisational frameworks as mentioned in the literature.

According to the literature, HR practises increase collaboration, innovation and decision – making, because of their impact on knowledge creation and sharing directly influence on the organisational performance. Farnese et al. (2019) and Singh and Gupta (2023) identify practises, such as performance appraisals, cross functional teamwork and leadership commitment, as drivers of improved performance.

In line with this perspective, the findings also showed a strong positive relationship between HR and Performance with a path coefficient of 1.047. It follows that this relationship is statistically significant to very high degree as evidenced by the exceptionally high T statistics (150.165) and the negligible p value (0.000). Results of this alignment are in line with the literature and they contribute to the view that HR practises themselves have a direct impact on performance results through the development of an adaptive and knowledge driven organisational culture. This result confirms the role of HR as a performance enabler as stated in literature.

Knowledge creation, knowledge sharing, and knowledge retention help improve performance, which has been the centre of extensive discussion in literature with respect to the role of KM. Effective KM practises are associated with innovation, efficiency, improved decision-making and eventually performance (Grimsdottir and Edvardsson, 2018; Dahiya, 2023). A critical framework referred to as the SECI model, which provides dynamic interaction between tacit and explicit knowledge for ongoing improvement is highlighted.

The results however deviate from the literature by indicating a weak and negative Statistical relationship between Knowledge and Performance (path coefficient = -0.052). Even though the relationship is statistically significant (T statistics shows 6.259 and p value shows 0.000), there is a very small effect size and direction of the effect is negative which providing evidence that some fundamental limitations or inefficiencies may exist when being utilising or applied knowledge within the context of the study. The difference in findings between the two studies suggests that factors, including lack of knowledge quality, mismatch with organisational goals, or inappropriate KM mechanisms, may be eroding KM's positive effect on organisational performance.

Comparative analysis shows reinforced vision of HR as a key player to stimulate knowledge and performance. However, the knowledge and performance relationship was weak and negative, an exception. It implies that HR practises do indeed support knowledge management but that contextual factors not described in the literature or inefficiencies in knowledge application processes constrain the translation of knowledge into performance outcomes.

Consequently, this discrepancy should be resolved further investigation on the practical implementation of KM strategies, the quality and relevance of knowledge share, and on the possibility of obstructing the effective knowledge use are recommended. The understanding of the intricacies of KM can help close the gap between what is expected from theoretical perspective and what is observed in terms of outcomes contributing to overall impact of KM on organisational performance.

Conclusion

7.1 Conclusion

The critical roles that guided the study were the roles of Human Resource Management (HRM) and Knowledge Management (KM) on performance of organisational in the Manufacturing industry. The results supported the first hypothesis (H1), stating that HRM has a strong and statistically significantly positive impact on organisational performance. This result revealed that HR practises (recruitment, training, performance appraisal, and collaboration) enhance innovation, decision making, and operational efficiency, which improved Organisational Outcomes.

Analysis further supported the second hypothesis (H2) in so far as that the results showed a robust positive relationship between HRM practises and KM. This finding provided further evidence that HRM has a crucial role to play in creating a knowledge oriented culture and facilitating related processes for knowing acquisition, sharing, and retention. In addition, HR initiatives, which may include incentivising knowledge sharing behaviours, creating collaborative tools, and supporting cross functional teamwork were identified as important enablers of KM effectiveness.

But the third hypothesis (H3) came out to be somewhat nuanced. The relationship between KM and organisational performance was statistically significant, although the weak and negative path coefficient indicated that KM practises were not transforming to performance gains at all as anticipated. Finding this out implied that there might be some inefficiencies or misalignment going on within the manufacturing industry with respect to how their knowledge was being used. This outcome could be explained by, among other things, the relevance or quality of the knowledge, or systemic barriers in knowledge utilisation.

The results confirmed the central role of HRM in improving both KM and organisational performance and revealed that the high impact of KM on performance needs more focus. The insights in these results reinforce the need of the combined impact of HRM and KM strategies in achieving organisational success.

7.2 Recommendations

- Enhance Knowledge Utilisation Mechanisms: To meet this need organisations should implement systems that can provide assurance as to whether knowledge generated and shared is actionable or not, particularly in light of the organisation's direction. Potential gaps should be addressed through regular knowledge quality and relevance audits.
- Invest in Technology for KM: In order to further streamline knowledge sharing processes and make such knowledge accessible across departments, it is necessary to adopt advanced digital platforms and tools, namely AI – driven knowledge repositories and collaboration software.
- Strengthen HRM Practices: The HR departments can then concentrate their energy towards the creation of a knowledge centric culture through inclusion of

knowledge sharing behaviours in performance appraisals, providing tailored training programmes, and cultivating interdepartmental learning.

- Foster Leadership Commitment: KM leaders should practise what they preach, by showing their commitment to knowledge sharing activities and make sure that the KM runs in sync with the wider organisational objectives.
- Monitor KM Impact: To assess the effectiveness of KM practises for driving performance outcomes, organisations should set metrics. Feedback loops help continuously identify and correct inefficiencies into application of knowledge.
- Encourage a Learning Organisation: Organisations that promote risk-taking, experimentation and continuous improvement can use tacit and explicit knowledge to be dynamic leverage to promote innovation and competitiveness.

By adopting these recommendations, the manufacturing industry can better integrate HRM and KM strategies, address current inefficiencies, and achieve sustainable improvements in organisational performance.

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