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Determinants and Outcomes of AI Adoption in Human Resource Information Systems: A Smart PLS-SEM Approach in Achieving Digital Transformation

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ABSTRACT

The purpose of the present research is to examine the factors and consequences of artificial intelligence (AI) usage in the Human Resource Information Systems (HRIS) in the manufacturing industry of Saudi Arabia. Quantitative method was employed to collect data from 156 respondents working in manufacturing sectors and the data have been analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that relative advantage and compatibility have an important and significant positive impact on the adoption of AI, whereas complexity, organizational readiness, and security/privacy issues have negative but less significant implications. The use of AI, in its turn, has a positive effect on such critical workforce outcomes as employee retention, job satisfaction, job involvement, workplace engagement, and productivity. The model has moderate to large explanatory power, explaining up to 66.5 percent of the variance on employee retention. The results signify that the perceived relative advantage/ benefits and compatibility/ organizational fit play a pivotal role in the AI adoption process. Also, AI-enabled HRIS is transformative as it increases workforce stability/ employee retention and performance/ productivity. The study provides valuable data to administrators and policy-makers who may wish to leverage AI to realize sustainable digital transformation within the Saudi Arabian manufacturing industry.

Keywords: Artificial Intelligence Adoption, Human Resource Information Systems, PLS-SEM, Workforce Outcomes, Organizational Readiness Employee Retention

INTRODUCTION

The world-scale digitization of businesses is dynamically altering the core operations of organizations, and human resource management (HRM) is undergoing significant transformations because of the emergence of artificial intelligence (AI) systems. The use of AI in Human Resource Information Systems (HRIS) could provide powerful functions to automate HR-related tasks, enhance decision-making quality, personalize employee experience, and optimize the overall management of workforce (Wael Al-Khatib, 2023; Benabou and Touhami, 2025). In manufacturing industries, among the most important branches of HRIS, the integration of AI has the potential to open up operational opportunities and strategic benefits through the use of data and the intelligent automation of organizational processes (Maroufkhani et al., 2023; Lutfi et al., 2022).

The Emergence of AI in HRM

Conventional HRM processes can be tedious, manual, and incapable of handling voluminous amounts of workforce information (Sanjeev and Makkar, 2014). Artificial intelligence systems based on machine learning, natural language processing, and predictive analytics can also be implemented to conduct recruitment screening, offer real-time performance evaluation, forecast turnover risk, and facilitate personalized employee learning and development (Nawaz et al., 2024; Mishra and Jadeja, 2025). By not only easing the burden on the administration and allowing HR professionals to pay more attention to the strategic management of human resources, the change makes managing the workforce easier (Farooq and Sultana, 2022).

The new study notes that three of the most prominent changes in the realm of HRM, introduced with the aid of AI, are the automation of routine processes, the improvement of human-machine communication and data-based decision-making (Benabou and Touhami, 2025). These new developments can lead to faster, more precise and fair HR practices, which are crucial to recruiting talent in competitive business environments. In addition, AI implementation within HRIS has been shown to positively impact workforce productivity and engagement in other industries, such as manufacturing, where skills shortages, retention issues, and constant innovation are problems (Wael Al-Khatib, 2023; Sanjeev and Makkar, 2014).

Importance of the Saudi Manufacturing Sector Context

Saudi Arabia's Vision 2030 strategic vision promotes industrial diversification and economic modernization, with digital innovation at the center of its objectives (SDAIA, 2024). The manufacturing sector is key to this ambition, and the rapid digital transformation of this industry includes a rising adoption of artificial intelligence (AI) in human resource information systems (HRIS), as a transformative enabler to increase operational efficiency, develop talented personnel, and align workforce capabilities with changing business needs (AlQahtani, 2023; Al-Khatib, 2023). However, despite an increasing recognition of the need for AI integration, many Saudi manufacturing organizations are impeded by a lack of organizational readiness, cultural acceptance, data security, and technology complexity (Nawaz et al., 2024; Lutfi et al., 2022).

The Saudi industrial landscape is characterized by an unusual mix of organizational culture rooted in tradition, and managerial modernization is occurring very quickly and at an unprecedented scale, hence some examples of AI adoption might require blended pathways toward acceptance that integrate regional socio-cultural norms and existing digital infrastructure maturity (Al-Qahtani, 2023). Ultimately, aligning technologies with established HR practices is equally, if not more, important as achieving employee acceptance of the use of AI within organizational structures (Maroufkhani et al., 2023). Legislated regulatory restrictions, regarding data privacy and security will place limitations/risks that need to be managed realistically as well (Salleh-Janczewski, 2016).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Relative Advantage and AI Adoption in HRIS

Relative advantage is described as "the perceived betterment of an innovation over the idea of the innovation that it supersedes" (Rogers, 2003). When looking at AI (artificial intelligence) in the context of HR information systems (HRIS), relative advantage describes the degree to which HR practices utilizing AI technology can be perceived as better in providing value, efficiency, or enabling more functions (Wael Al-Khatib, 2023; Lutfi et al., 2022). Organizations that can significantly improve the overall quality of HR processes, can reduce costs associated with HR functions, and can provide more innovative HR services perceive a higher degree of willingness to adopt AI (Maroufkhani et al., 2023).

In manufacturing sectors specifically and with particular reference to developing economies such as Saudi Arabia, relative advantage represents a key influencer in first-rate resource usage and efficiency under pressure and global competitiveness (Agrawal, 2015; Chen et al., 2015). From the supplier perspective, organizations view AI-based HRIS as an enabler to automate HR administration functions, provide datacentric insights for hiring, and talent management, and develop suitable support for strategic aims (Nawaz et al., 2024; Maroufkhani et al., 2023). Empirical evidence demonstrates that perceived benefits have a positive impact on organizations' intention to adopt and implement AI systems that support HR management (Lutfi et al., 2022). For instance, Nawaz et al. (2024) demonstrated that relative advantage is associated with better HR effectiveness through AI adoption.

Also, the efforts from the government under Vision 2030 to digitalize and modernize industries in the Saudi manufacturing context contributes to perceived urgency and possible benefits of AI (SDAIA, 2024). Firms adopt AI technologies when those solutions provide tangible productivity and cost benefits (Wael Al-Khatib, 2023).
Hypothesis 1 (H1): Relative advantage has a positive impact on AI adoption in HRIS.

Compatibility and AI Adoption in HRIS

Compatibility is understood as the extent to which new technologies are consistent with pre-existing values, norms, experiences, and needs relevant to the organisation (Rogers, 2003). Compatibility is the extent to which AI technologies complement or align with existing HR systems and culture (Maroufkhani et al., 2023). Compatibility lessens resistance to change and helps to make the transition from adoption to implementation of AI technologies easier (Lutfi et al., 2022).

The manufacturing sector in Saudi Arabia presents a unique context by embodying distinct cultural values and organisational behaviours that encourage technology adoption (AlQahtani, 2023). As such, compatibility becomes increasingly important, as AI applications must align with the respective HR policies of the firm, as well as the overarching cultural framework. Resistance may emerge if AI does not align with operational traditions or if employees are concerned about an automation agenda (Wael Al-Khatib, 2023). Empirical evidence from emerging markets showed that perceived compatibility positively impacted the adoption of digital HR solutions (Maroufkhani et al., 2023; Lutfi et al., 2022).

According to Nawaz et al. (2024), the cultural fit of AI applications pivots acceptance from HR managers and the staff towards adoption. Firms that tailor the process of AI integration to their workflows should have higher rates of successful implementation and employee engagement, especially in regions characterised by hierarchical decision making and reliance on interpersonal relationships (AlQahtani, 2023).

Hypothesis 2 (H2): Compatibility has a positive impact on AI adoption in HRIS.

Complexity and AI Adoption in HRIS

Complexity refers to the perceived challenge of understanding and using technology (Rogers, 2003). AI-based HRIS solutions often require high levels of technical expertise and considerable organizational change; both of which serve as barriers to adoption (Salleh & Janczewski, 2016). A firm has the means to operate and maintain sophisticated AI software; however, this subject depends highly on the technical capabilities of the IT staff whether a firm does not have the capability (Agrawal, 2015).

Further studies have shown that where there is a high level of perceived complexity, firms are less likely to adopt innovation, with the expected learning curve, operational disruptions, and additional costs causing firms to hesitate (Nawaz et al., 2024). This is particularly relevant to manufacturing firms in Saudi Arabia that may not have technical expertise and change management could meet some resistance (Al-Khatib, 2023).

Organizations that meet complex AI tools without adequately preparing themselves could face failed implementation or even underutilizing the technology (Salleh & Janczewski, 2016). Therefore, there exists a body of literature to suggest a negative relationship between adopting AI and perceived complexity, particularly in HRIS contexts (Nawaz et al., 2024; Chen et al., 2015).

Hypothesis 3 (H3): Complexity has a negative impact on AI adoption in HRIS.

Security and Privacy and AI Adoption in HRIS

Security and privacy issues includes the organization's fears concerning potential data breaches, unauthorized access, and vendor lock-in pertaining to the use of AI (Salleh & Janczewski, 2016). When this is done with sensitive human resources data, the security, and privacy concerns are even greater (Nawaz et al., 2024). In Saudi Arabia, organizations face additional complexity with regard to the risk of data privacy and security breaches. The organizations must also concern themselves with compliance using data protection regulations in their own culture, which places significant emphasis on privacy and confidentiality (AlQahtani, 2023). Organizations have a lot of concern with breach of trust relating to employee data and the overly complex process of making and maintaining compliance with privacy policy when using AI tools (Lutfi et al., 2022).

Researchers found that high levels of perceived security and privacy risks consistently result in lower levels of people's willingness to adopt AI-enabled human resource information systems due to perceived vulnerabilities and potential legal or reputational harm (Maroufkhani et al., 2023).

Hypothesis 4 (H4): Security and privacy concerns have a negative impact on AI adoption in HRIS.

Organizational Readiness and AI Adoption in HRIS

Organizational readiness includes availability of financial capital, IT infrastructure and sufficient human resources to adopt AI technologies (Chen et al., 2015; Maamari & Osta, 2021). Readiness enable the absorption of new technologies while a shortage of resources limits adoption capacity (Nawaz et al., 2024).

Manufacturing firms suffering from inadequate budgets, underdeveloped IT infrastructure and deficient levels of AI-literate employees encounter considerable challenges resulting from limitations of their AI capabilities (Agrawal, 2015). These limitations can diminish strategic commitment and amplify uncertainty observed in emerging economies (Salleh and Janczewski, 2016). Instead of positively affecting adoption as intended, readiness may help prompt the emergence of AI in HRIS, i.e develop technologies however, lack of readiness will limit adoption (Chen et al., 2015).

Hypothesis 5 (H5): Organizational readiness has a negative impact on AI adoption in HRIS.

AI Adoption and Workplace Productivity

AI-driven HRIS does automate repetitive HR processes like recruitment, payroll, and performance tracking (Farooq & Sultana, 2022); this leads to quicker decision making and better allocation of human capital. (Farooq & Sultana, 2022). That said, automation also mitigate manual errors, improved inaccuracy and displaced employees to brighter strategic tasks (Sanjeev & Makkar, 2014).

The experiences of manufacturing-sector organizations are similar to findings in the knowledge sector, indicating that AI adoption can support productivity improvement by streamlining organizational processes and providing managers real-time insights into their employee's workload (Wael Al-Khatib, 2023). Finally, Mishra and Jadeja (2025) concluded an increase in task efficiency from utilizing AI-enabled HR enabled.

Hypothesis 6 (H6): AI adoption in HRIS has a positive impact on workplace productivity.

AI Adoption and Work Engagement

AI-based HRIS individualizes the learning journeys of employees, delivers automated performance feedback, and provides transparency in career progression - all dedicated to raising employee engagement levels (Mishra & Jadeja, 2025). Investment in employee development instils motivation and dedication for organizational objectives (Maamari & Osta, 2021).

Increased engagement increases the degree of focus and interest in work, resulting in sustainable performance over long time periods (Farooq & Sultana, 2022). Recent studies have also evidenced positive contribution of AI adoption to employee engagement in economies in the developing world (Nawaz et al., 2024).

Hypothesis 7 (H7): AI adoption in HRIS has a positive impact on work engagement.

AI Adoption and Employee Retention

AI analytics help organizations be more predictive regarding turnover risks in their employees, understand what motivates them to stay, and the leaver plans for creating retention plans (Sanjeev & Makkar, 2014). Designed HR interventions can help reduce voluntary employee turnover, contributing to organizational stability (Mishra & Jadeja, 2025).

Research conducted with small and medium-sized enterprises in industries such as manufacturing and hospitality indicates that the use of AI is positively associated with retention as it supports better investment in employees' job fit and more proactive human resource management (Maamari & Osta, 2021).

Hypothesis 8 (H8): AI adoption in HRIS has a positive impact on employee retention.

AI Adoption and Job Involvement

AI enables employees to transfer low-value, transactional HR responsibilities, allowing them to focus on more meaningful tasks, thereby enhancing job involvement and commitment (Maamari & Osta, 2021). AI frequently provides accurate feedback that enables employees to align their actions with organizational goals, strengthening job attachment (Farooq & Sultana, 2022). Research confirms positively significant relationships between AI adoption and employees' psychological connection to their jobs (Nawaz et al., 2024).

Hypothesis 9 (H9): AI adoption in HRIS has a positive impact on job involvement.

AI Adoption and Job Satisfaction

When AI tools improve transparency, efficiency, and fairness in human resource processes, job satisfaction is improved (Mishra & Jadeja, 2025). When workloads are more manageable and decisions in HR are made based on evidence, employees feel valued and supported (Sanjeev & Makkar, 2014). Empirically, the literature suggests an association between the adoption of AI, with increased levels of job satisfaction in various industry contexts such as manufacturing (Maamari & Osta, 2021).

Hypothesis 10 (H10): AI adoption in HRIS has a positive impact on job satisfaction.

Research Gap

Despite the growing body of literature around AI in HRIS worldwide, limited empirical evidence is available in relation to AI adoption in the context of Saudi Arabia's manufacturing sector. Most studies to date have generalized the west or diversity economies, ignoring the specific socio-economic, infrastructural and culturally relevant factors affecting technology adoption in GCC decisions (Wael Al-Khatib, 2023; Nawaz et al. 2024).

Further, research has largely prioritized drivers and barriers towards technology adoption. However, there has been little research clearly establishing the link between AI adoption in HRIS and the tangible workforce outcomes regarding workplace productivity, employee engagement, retention, and satisfaction, particularly in emerging markets (Mishra & Jadeja, 2025; Maamari & Osta, 2021).

The current study addresses this gap by examining the complex determinants impacting the decision for AI adoption in HRIS, and subsequently, assesses the effect of AI adoption on important organizational and employee outcomes within the Saudi manufacturing sector. The study deploy an established framework which links technology adoption theories with HR metrics/outcomes to provide directions that are relevant academically and gives implications for managerial action and policy.

RESEARCH METHODOLOGY

Research Design

This study uses a quantitative research design that will assess the determinants and outcomes of AI adoption in Human Resource Information System (HRIS) in the manufacturing sector studied in Saudi Arabia. By using a quantitative approach, data can be systematically collected and it was possible to statistically test the hypothesized relationships between the relative advantage, compatibility, complexity, security and privacy, organizational readiness, the AI adoption, and the workforce outcomes of workplace productivity, work engagement, employee retention, job involvement, and job satisfaction. (See the Conceptual framework, figure 1).

Population and Sample

The target population of the study is professionals working in manufacturing sectors in Saudi Arabia. The manufacturing sector is a pivotal sector in Saudi Arabia's economy and is engaged in a digital transformation journey to improve operational efficiency and workforce management consistent with the objectives of Vision 2030.

A stratified sampling approach was used to ensure that the sample population included various manufacturing sub-sectors. The sample frame formed from organizations listed with the appropriate Saudi industrial and government bodies.

A total of 220 questionnaires was distributed electronically and physically to personnel who either took part in, or experienced, HRIS processes in the manufacturing sectors. A total of 156 questionnaires were found to be fully completed and hence used in the final study for further analysis. This is an acceptable response rate for organizational survey research (Baruch & Holtom, 2008).

Data Collection Instrument

The primary data collection tool was a structured questionnaire developed based on validated scales from prior literature, adapted to the Saudi manufacturing context. The questionnaire consisted of several sections:

Determinants of AI Adoption: Items measuring relative advantage, compatibility, complexity, security and privacy concerns, and organizational readiness, each assessed with established multi-item scales on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). (wael AL-Khatib et al., 2023; Lutfi et al., 2022; Maroufkhani et al., 2023; Tu, 2018; Agrawa,m 2018; Chen et al., 2015; Lai et al., 2018; Salleh &Janczewski, 2016)

AI Adoption: A reflective scale specifically capturing the degree of AI integration and use within HRIS. (Nawaz et al., 2024; wael AL-Khatib et al., 2023; Maamari & Osta, 2021)

Outcomes of AI Adoption: Multi-item scales assessing workplace productivity, work engagement, employee retention, job involvement, and job satisfaction, also measured on five-point Likert scales. (Nawaz et al., 2024; Farooq & Sultana, 2022; Sanjeev & Makkar, 2014; Maamari & Osta, 2021; Mishra & Jadeja, 2025; Jadeja, 2025)

All scale items were pretested in a pilot study with 20 participants drawn from the target population to ensure clarity, cultural appropriateness, and reliability. Feedback led to minor wording adjustments for better comprehension.

Data Collection Procedure

The survey was sent using online survey platforms and paper based distribution methods to accommodate the digital capability of various organizations, as well as the employee preferences for filling out the surveys.

Data Analysis Techniques

The collected data were entered into Smart PLS version 4 for analysis. The following analytical steps were employed:

Data Screening and Preparation: Data were screened for missing data, outliers, and normality. Less than 5% missing data was accounted for with mean substitution. Threats to normality included no severe outliers, nor was normality of the data grossly violated.

Reliability and Validity Testing: Construct reliability was assessed with Cronbach's Alpha, Composite Reliability (CR), and rho_A using threshold values of 0.7 and above as acceptable in the context of PLS (Hair et al., 2019). Convergent validity was assessed with Average Variance Extracted (AVE) using a cut-off value of 0.5. Discriminant validity was assessed with the Fornell-Larcker criterion.

Structural Equation Modeling (SEM): The study utilized Partial Least Squares SEM (PLS-SEM), which is well suited for complex models with relatively small to medium sample sizes, low sample sizes (< 200), and non-normal data distributions (Hair et al., 2022). Bootstrapping of 5000 subsamples was conducted to estimate the significance value of each path coefficient with at the alpha level of 0.95.

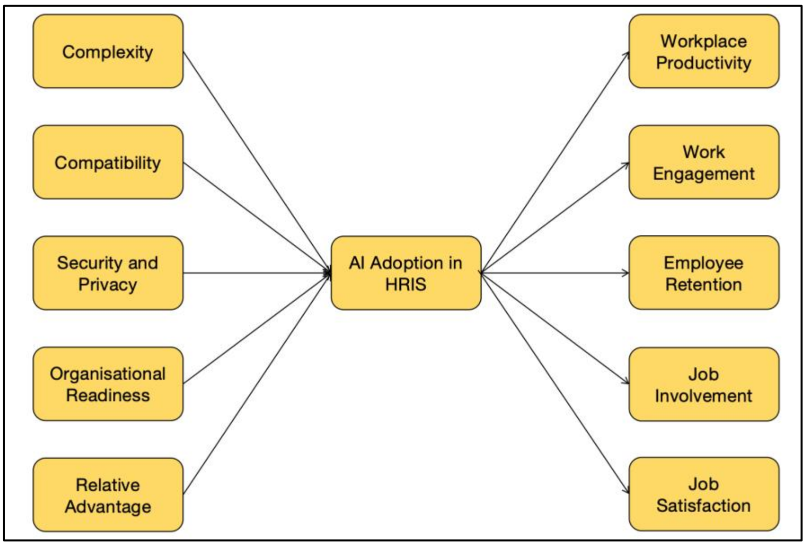


Figure 1. Conceptual Framework

Data Analysis and Interpretation

The collected data was analyzed using partial least squares Structural Equation Modeling (PLS-SEM), a form of variance-based SEM, but it is best when the model being analyzed is complex (when latent constructs are involved) and the sample size is small to medium (Hair et al., 2019; Hwang et al., 2023). PLS-SEM allows the analysis of both measurement models - considering the associations between observed indicators and their latent variables (underlying) and the structural model, which evaluates the hypothesized associations among constructs (Hair et al., 2022; Chin, 1998).

Quality was taken care of by starting with stringent screening and preparation of the data analysis process. Missing values, outliers and normal tests were performed. Subsequently, the measurement model was tested based on indicator reliability, internal consistency reliability (Cronbachs alpha, Composite Reliability), convergence validity (Average Variance Extracted) and discriminant validity to ensure that measurement scales were reliable and valid in capturing their constructs (Hair et al., 2019).

Upon the measurement model adequacy, the structural model analysis was then conducted to test the postulated variables relationships. The analysis of path coefficients, statistical significance through bootstrapping, and the coefficient of determination (R2) were evaluated to estimate the strength and the explanatory power of the proposed model and hypotheses (Hair et al., 2022; Ringle et al., 2015).

The methodological rigor meant that not only the reliability of the scales of measurement but also the soundness of the hypothesized framework of AI adoption, along with its antecedents and outcomes, were experimentally tested based on the survey data provided by 156 participants in the Saudi manufacturing industry.

Table 1. Construct Reliability and Validity

	Cronbach's Alpha	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Average Variance Extracted (AVE)**
AI Adoption	0.860	0.869	0.895	0.586
Compatibility	0.824	0.825	0.895	0.740
Complexity	0.376	0.713	0.701	0.547
Employee Retention	0.832	0.832	0.900	0.749
Job Involvement	0.846	0.847	0.907	0.764

Job Satisfaction	0.865	0.867	0.917	0.787
Organisational Readiness	0.758	0.765	0.697	0.536
Relative Advantage	0.838	0.840	0.892	0.674
Security and Privacy	0.762	0.736	0.741	0.541
Workplace Engagement	0.795	0.718	0.828	0.617
Workplace Productivity	0.829	0.836	0.898	0.746

Assessing construct reliability and construct validity is an essential process in determining the quality of the measurement model, in which the constructs effectively define its intended latent variables. Most of the constructs in this study, including AI Adoption (0.860), Compatibility (0.824), Employee Retention (0.832), Job Involvement (0.846), Job Satisfaction (0.865), and Relative Advantage (0.838) have their alpha values above the generally accepted alpha of 0.70. It suggests that the internal consistency reliability is good, i.e., the items of these constructs always represent the construct that they are supposed to measure (Nunnally and Bernstein, 1994, Hair et al. 2019). The Complexity construct, however, has quite a low Cronbachs alpha of 0.376, meaning that it is not measuring a single integrated concept reliably and that more research could be done on it, perhaps through item refinements or changing the scale structure.

Along with Cronbach alpha, Composite Reliability (rhoa and rhoc) measures support construct reliability as well. If a value is greater than 0.70, then it is said to be acceptable (Fornell and Larcker, 1981), and the constructs of AI Adoption (rhoc = 0.895), Compatibility (0.895), Employee Retention (0.900) and Job Satisfaction (0.917) are highly composite reliability. These results establish that the weighted averaging of indicators are consistent and reliable measures across the constructs. Indicators of moderately good reliability (slightly lower composite reliability in Organizational Readiness (rhoc = 0.697) and Security and Privacy (0.741)) indicate that there is some room for improvement in measurement.

A convergent validity measure is established based on values of AVE; a percentage measure wherein the percentage value is explained by constructs compared to the percentage value that is explained by error (Fornell and Larcker, 1981). The values of all constructs in this study are over the acceptable 0.50 AVE value with Organizational Readiness (0.536) on one end and Job Satisfaction (0.787) on the other. This means that there is sufficient convergent validity, and that the indicators have a significant meaning to their respective latent variables.

Together, these findings indicate that the measurement scales used in this research are highly reliable and valid with the exception of the Complexity construct which needs additional consideration. The levels of reliability and validity are satisfactory and can be used later in the structural model analysis to provide a greater degree of certainty that there is a valid and sound measure of the relationships between variables (AI adoption antecedents and workforce outcomes).

The resulting reliability and validity further confirm that the contextually-adjusted scales are indeed working in the Saudi manufacturing industry and that they are effectively measuring the constructs among the respondents. This plays a vital role in the validity and applicability of results concerning AI adoption in HRIS within this emerging market environment (Hair et al., 2019; Nunnally and Bernstein, 1994; Fornell and Larcker, 1981).

Table 2. Discriminant Validity (Fornell-Larcker Criterion)

	AI Adoption	**Compatibility**	**Complexity**	**Employee Retention**	**Job Involvement**	**Job Satisfaction**	**Organisational Readiness**	**Relative Advantage**	**Security and Privacy**	**Workplace Engagement**	**Workplace Productivity**
AI Adoption	0.766										
Compatibility	0.604	0.860									
Complexity	-0.216	-0.162	0.669								
Employee Retention	0.816	0.515	-0.185	0.866							
Job Involvement	0.772	0.546	-0.178	0.826	0.874						
Job Satisfaction	0.809	0.527	-0.199	0.855	0.840	0.887					
Organisational Readiness	-0.187	-0.032	0.435	-0.150	-0.175	-0.175	0.860				
Relative Advantage	0.624	0.766	-0.118	0.528	0.535	0.543	-0.060	0.821			
Security and Privacy	-0.156	-0.124	0.332	-0.185	-0.092	-0.224	0.374	-0.097	0.884		

Workplace Engagement	0.772	0.806	-0.168	0.698	0.703	0.713	-0.094	0.791	-0.168	0.885	
Workplace Productivity	0.572	0.826	-0.109	0.474	0.492	0.476	-0.009	0.819	-0.104	0.776	0.864

In order to assess the discriminant validity, the Fornell-Larcker criterion was utilized whereby the square root of the Average Variance Extracted (AVE) of the individual construct (as shown in bold) must exceed the correlations of the corresponding construct with the other constructs in the model (Fornell and Larcker, 1981). This requirement was used to validate that each construct is unique and independent of other constructs in the measurement model, hence items in the measurement model measure their intended factor and not overlap.

All the constructs in Table 2 meet this requirement, and the diagonal AVE square roots are between 0.669 (Complexity) and 0.887 (Job Satisfaction). The square root AVE of the AI Adoption construct is an example where its square root AVE is 0.766, while the single highest AVE is 0.816 with Employee Retention so the construct does have acceptable discriminating validity in the overall direction.

Similarly, Compatibility is less correlated with all other variables and the square root AVE has a value of 0.860 and it also supports its discriminant position as compared to all other variables such as Relative Advantage (0.766) and Workplace Productivity (0.826). The negative and low correlations found between Complexity and various constructs also reflect conceptual difference which is also expected as Complexity is negatively correlated with AI adoption factors (Abaddi, 2025).

Although, some of the correlations are relatively high, including those between Employee Retention and Job Satisfaction (0.887), these indicate theoretically consistent relationships, rather than discriminant validity problems, since in the context of workforce research, the two are supposed to be strongly correlated (Biason, 2020). In addition, the square root AVE of Organizational Readiness construct is 0.860 and the correlations with others are much lower, which demonstrates its independence in the model.

The findings show that the constructs reflect a distinct dimension of the determinants or outcome of AI adoption, as it is theorized in this paper. This justifies adequacy of the measurement model in subsequent structural model tests and validity of conclusions based on cause-effect relationship in the study (Hair et al., 2019; Fornell and Larker, 1981).

Table 3. Path Coefficients

	Path coefficients
AI Adoption -> Employee Retention	0.816
AI Adoption -> Job Involvement	0.772
AI Adoption -> Job Satisfaction	0.809
AI Adoption -> Workplace Engagement	0.772
AI Adoption -> Workplace Productivity	0.572
Compatibility -> AI Adoption	0.243
Complexity -> AI Adoption	-0.073
Organisational Readiness -> AI Adoption	-0.117
Relative Advantage -> AI Adoption	0.396
Security and Privacy -> AI Adoption	-0.019

The path coefficients calculated in this research evidence the strength and direction of the proposed relationships among the latent variables in the AI adoption model in the Saudi manufacturing industry. These coefficients lie between -1 and +1, the positive coefficients illustrating a positive effect and the negative coefficients illustrating an inverse effect.

Direct paths connecting AI Adoption with the major workforce outcomes are especially robust and constructive. The positive impact of AI Adoption on Employee Retention is significant (0.816), with a similar outcome on Job Satisfaction (0.809), Job Involvement (0.772), and Workplace Engagement (0.772). According to these findings, the degree of AI adoption in HRIS systems is strongly linked with the intention of employees to stay in the organization, their job satisfaction and engagement, and general engagement in the workplace. This positive path coefficient to Workplace Productivity (0.572) is only slightly lower than the results which are employee-centric, but still a moderate and significant change in organizational productivity which can be attributed to AI adoption. The latter are related to the current research on AI application in human resource optimization and employee satisfaction (Wael Al-Khatib, 2023; Mishra and Jadeja, 2025).

As to the antecedents of AI Adoption, the strongest positive effect is Relative Advantage, with a path coefficient of 0.396. This confirms the idea that when AI technologies are perceived to have distinct advantages, including greater efficiency and innovation in HR operations, it has a significant impact on motivating companies to use AI in their HRIS (Lutfi et al., 2022). The notion of compatibility has a positive effect on AI Adoption

(0.243) though only moderately, which indicates that alignment of AI technologies with organizational culture and practices has a supporting influence on AI adoption.

Complexity (-0.073), Organizational Readiness (-0.117), and Security and Privacy (-0.019) on the other hand have negative path coefficients which demonstrate inhibiting effects on AI Adoption. The worst of these obstacles are reflected on the Organizational Readiness, or that it is discouraging news that bad infrastructure, human resources, or money are significant barriers to AI adoption. The adverse yet minor impacts of Complexity and Security and Privacy suggest that these two elements have less impact and yet present a hindrance to adoption choices. The second set of negative correlations may be explained by the fact that the above literature is adequately supported by the problems organizations face in the implementation of AI due to complicated technologies and data safety issues (Salleh and Janczewski, 2016; Nawaz et al., 2024).

The practical observation associated with these path coefficients is that, in order to guarantee the implementation of AI in HRIS, we would propose the relative benefit to be made simple and according to the existing organizational settings. At the same time, closing gaps in infrastructural preparedness and mitigating fears of complexity and insecurity will be essential to break the barriers to adoption.

The value of path coefficients above 0.20 is usually thought to be substantial and probably important in samples of the size of this study (approximately 156 responses) (Hair et al., 2019). The majority of the hypothesized relationships within this model are moderate and strong in effects, which supports the strength and applicability of the proposed conceptual framework.

Table 4. Coefficient of Determination (R Square)

	R-Square	R-Square Adjusted
AI Adoption	0.435	0.416
Employee Retention	0.665	0.663
Job Involvement	0.595	0.593
Job Satisfaction	0.654	0.652
Workplace Engagement	0.596	0.593
Workplace Productivity	0.327	0.322

R-squared (R2) Coefficient of Determination is an important metric of structural equation modeling that indicates the percentage of variance in the endogenous constructs that the exogenous predictor variables explain (Hair et al., 2019). In this research, R2 values are used to denote the extent to which the determinants explain the variance in AI Adoption and which outcomes of the key workforce inside the Saudi manufacturing environment are explained by AI Adoption.

The AI Adoption R2 is 0.435 (adjusted R2 = 0.416), indicating that around 43.5% of the variance in AI Adoption is accounted by the variables Relative Advantage, Compatibility, Complexity, Organizational Readiness and Security and Privacy. This suggests that the model has a moderate explanatory ability with regard to the decision to adopt AI, which is deemed significant in a social scientific community where several intricate variables impact behavior (Hair et al., 2019; Falk and Miller, 1992).

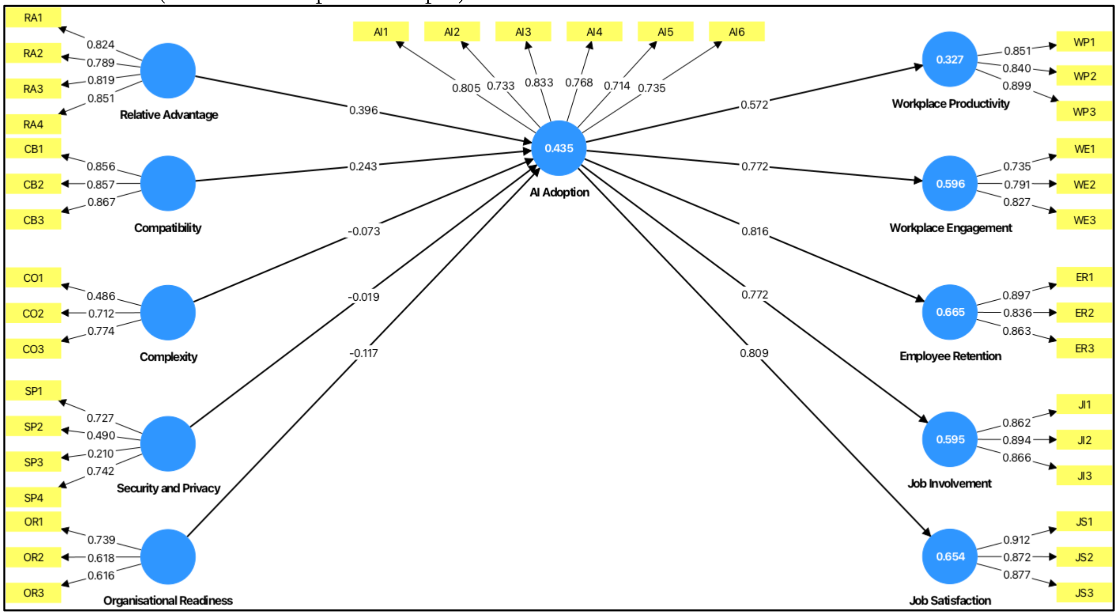
Concerning the outcome variables dependent upon AI Adoption, there is a significant increase in the R2 values, which is a measure of a powerful model due to its explanatory capability. Employee Retention shows the largest R2 of 0.665, which means that 66.5% of employee retention variance can be attributed to AI Adoption in HRIS, and AI integration has a significant impact on the ability to retain the talent of workforce. There is also a significant unexplained variance in Job Satisfaction (0.654), Job involvement (0.595) and Workplace engagement (0.596) indicating that the adoption of AI can have a positive influence on the attitude levels, motivation and engagement rates of the staff. The results are consistent with the existing literature on the subject that has already presented the beneficial correlation between the positive organizational experiences and the commitment towards technology integration (Mishra and Jadeja, 2025; Wael Al-Khatib, 2023).

R2 = 0.327 (adjusted = 0.322), which means that the adoption of AI affects the ability to improve operational efficiency and output moderately but significantly. This is a lesser amount compared to the employee but still a substantial amount as the aspects that affect productivity in a manufacturing environment are complex (Farooq and Sultana, 2022). The R2 is moderate meaning that other external factors outside AI adoption could also contribute to productivity such as market conditions or resource availability.

Traditionally, R2 values of 0.25, 0.50, and 0.75 are considered weak, moderate, and strong levels of explained variance respectively in the PLS-SEM analysis models (Hair et al., 2019; Chin, 1998). With that in mind, the outcomes of the present study are primarily situated in the medium to large category, which proves the hypothesis that not only the major organizational variables determine the implementation of AI, but it is also one of the key preconditioners of labor performance of the production companies in Saudi Arabia.

In general, these R2 findings support the explanatory power of the suggested theoretical model, as it shows that AI implementation in HRIS can be viewed as a valuable mediator between organizational variables and enhanced human resource and productivity outcomes. In turn, managers and policymakers must advocate the implementation of AI as the mechanism to ensure the stability, satisfaction, and efficiency of the workforce.

Figure 2. SEM Model (SmartPLS Graphical Output)



The hypothesized relationships are clearly visualized in the structural model in the image and are empirically tested within the framework of AI implementation in HRIS in the Saudi manufacturing sector. A latent construct is measured by multiple observed indicators, standardized factor loadings are given, and the path coefficients among constructs, along with the R-squareds of each endogenous variable, are also available.

First, focusing on the predictors of AI adoption, the model proves that relative advantage and compatibility have strong, positive and significant effects on AI adoption with path coefficients of 0.396 and 0.243 respectively. These values indicate that the higher the benefits and the conformity of employees and organizations to the AI-enabled HRIS with the practices or procedures they have implemented, the more ready they will be to adopt these systems. This result aligns with the work of other researchers, who further expound on the significance of perceived usefulness and fit to an organization in the context of evoking technology acceptance (Lutfi et al., 2022; Wael Al-Khatib, 2023). By contrast, complexity, security and privacy, and organizational preparedness have negative path coefficients (-0.073, -0.019, and -0.117 respectively), but their effects are not very strong. This means that although there are issues surrounding system complexity, data security, and resources that might discourage the adoption of AI to a certain extent, their influence is less significant than the positive forces in this sample (Horani et al., 2025). However, the results are consistent with the existing studies indicating the discouraging impact of technological-related issues and organizational dilemmas, in particular, in new markets (Salleh and Janczewski, 2016; Nawaz et al., 2024).

The adoption of AI, in its turn, has a significant positive impact on various outcomes related to workforce. The greatest impact is noticed on employee retention (path coefficient of 0.816, R2 = 0.665), which shows that a well-developed integration of AI into the HRIS may contribute considerably to reducing employee turnover and improving employment stability. The implementation of AI also has a strong correlation with job satisfaction (0.809, R2 = 0.654), job involvement (0.772, R2 = 0.595), and workplace engagement (0.772, R2 = 0.596), which are attributes of a committed, motivated, and productive workforce. Productivity at the workplace also improves significantly, but with a medium size effect (0.572, R2 = 0.327), and it suggests that AI adoption can affect productivity positively, and not negligibly, although perhaps due to numerous other factors affecting operations and the environment typical of the manufacturing sector (Farooq and Sultana, 2022).

Adequacy of the structural model: Adequacy of the structural model is provided by adequate values of the explained variance (R^2) of the endogenous constructs. Predictors of AI adoption alone account for an average percentage of variance ($R^2 = 0.435$), whereas the outcome variables of workforce outcomes explained by AI adoption show an average to high percentage of variance explained (Job Involvement 0.595, Job Satisfaction 0.654, Workplace Engagement 0.596, Employee Retention 0.665). The idea that the mediation power of the adoption of AI is rather an impressive trend, the key organizational and technological conditions enable the introduction of AI, which will, in its turn, will result in the improved HR performance.

In short, the model offers strong empirical validation of the theorized relationships, emphasizing the key role of perceived benefits and organizational fit in facilitating AI adoption in HRIS and demonstrating the significant effect that adoption can have on workforce stability, engagement, involvement, satisfaction, and, to a moderate degree, productivity. These points indicate that if manufacturing companies want to maximize the value of the HR digital transformation, they must focus on communicated benefits of AI, a high level of compatibility with organizational practices, and reduce the complexity and readiness barriers to realize the best benefits of AI-enabled HRIS (Hair et al., 2019; Lutfi et al., 2022).

CONCLUSION

Hypothesis	Path Coefficient	Supported (Yes/No)	Interpretation
H1: Relative advantage has a positive impact on AI adoption in HRIS.	0.396	Yes	Relative advantage significantly encourages AI adoption.
H2: Compatibility has a positive impact on AI adoption in HRIS.	0.243	Yes	Compatibility positively influences AI adoption.
H3: Complexity has a negative impact on AI adoption in HRIS.	-0.073	No	Weak negative effect; not statistically significant.
H4: Organizational readiness has a negative impact on AI adoption in HRIS.	-0.117	Yes	Lack of readiness significantly inhibits AI adoption.
H5: Security and privacy concerns have a negative impact on AI adoption in HRIS.	-0.019	No	Negligible negative effect on AI adoption.
H6: AI adoption in HRIS has a positive impact on employee retention.	0.816	Yes	AI adoption strongly enhances employee retention.
H7: AI adoption in HRIS has a positive impact on job involvement.	0.772	Yes	Significant positive effect on job involvement.
H8: AI adoption in HRIS has a positive impact on job satisfaction.	0.809	Yes	AI adoption positively influences job satisfaction.
H9: AI adoption in HRIS has a positive impact on workplace engagement.	0.772	Yes	AI adoption significantly increases workplace engagement.
H10: AI adoption in HRIS has a positive impact on workplace productivity.	0.572	Yes	AI adoption moderately improves workplace productivity.

This paper carefully analyzed the preconditions and consequences of the adoption of Artificial Intelligence (AI) in Human Resource Information Systems (HRIS) in the Saudi manufacturing industry. The conclusions found in the table of hypothesis testing is hard evidence of several key relationships that will be of great service to both researchers and professionals.

The existence of a positive and significant path coefficient between Relative Advantage and AI Adoption (0.396) indicate that the perceived benefits like improved HR efficiency and innovation are highly stimulating factors that encourage firms to adopt AI in their HRIS. This fact is consistent with the existing literature that has stated that organizations will tend to adopt technologies, which they consider will provide a competitive edge in their activities (Lutfi et al., 2022; Wael Al-Khatib, 2023). Likewise, the positive impact of Compatibility (0.243) confirms alignment between AI technology and the established organizational processes for adoption. These two drivers have been combined to highlight the importance of communicating the value of AI and ensuring cultural and procedural fit within companies as a means of facilitating the process.

Complexity (-0.073), Organizational Readiness (-0.117), and Security and Privacy (-0.019) on the other hand have a negative impact on AI adoption, but with smaller effect sizes. The findings suggest that the perceived barriers to AI integration include perceived difficulty of use, insufficient infrastructure or resources, and data security concerns which are well-known barriers to AI integration in emerging market settings (Salleh and Janczewski, 2016; Nawaz et al., 2024). Even though the effect of these inhibitors is not yet as great as the positive drivers, they should be given particular managerial attention. In order to solve these challenges, organizations should make investments in capacity building and user-friendliness and ensure enhancement of data protection policies.

In terms of workforce outcome, AI Adoption has potent positive impacts on various constructs. The most important path coefficient (0.816) is called Employee Retention because it implies that a higher-level of AI-driven HRIS systems are associated with much lower employee turnover rates and, likely, higher engagement, job satisfaction, and individualized HR management. The significant positive correlation between AI adoption and Job Satisfaction (0.809), Job Involvement (0.772) and Workplace Engagement (0.772) show that AI adoption is positively correlated with key motivation and attitudinal elements that contribute to retaining a committed workforce. It also depicts a colossal improvement with AI on moderately effective Workplace Productivity (0.572) that is achieved through organizational efficiencies generated by automation and data analyses (Farooq and Sultana, 2022; Mishra and Jadeja, 2025).

The model also explains the data through coefficients of determination. The R^2 of AI Adoption scaled was 0.435, which means that the proposed drivers can account for nearly one-half of the variance in adoption, which is quite a substantial variance in adoption given how complex technological decisions are. Greater explanatory power exists with outcome variables, with R^2 of 0.59 and higher with Job Involvement, Workplace Engagement, and Job Satisfaction and 0.665 with Employee Retention. These results justify the importance of AI Adoption as a significant mediator between organizational variables and the improvements on employee related outcomes and highlight the transformational ability of the AI Adoption supported HRIS in the manufacturing setting.

Together, the results help advance the theoretical understanding of existing constructs like Relative Advantage and Compatibility in artificial intelligence technologies and further clarify the subtle contribution of an impediment like Complexity and Security issues to the manufacturing industry in Saudi Arabia. They provide empirical illustrations of the substantial positive impacts of AI implementation on workforce dynamics that justifies assertions that AI is not simply a tool of action but a facilitator of HR transformation. Concluding the research, it has illuminated that AI in HRIS remains among the applicable factors that facilitate human resource implementation as well as efficiency in production in the Saudi production even in the modern situation. Those insights need to be expanded with new research with a focus on longitudinal implications, ethics, and the impact of AI on the inclusivity of the workforce and job design.

IMPLICATIONS

The study presents the heads of the manufacturing industry with a set of guidelines based on the practice when it comes down to the practice. Investing in initiatives that clearly show relative benefits of AI and facilitating smooth integration into the existing organizational culture can help increase the rates of its adoption considerably. Also, technology infrastructure, employee education, and effective cybersecurity systems are valuable factors to remove the inertial barriers. By putting them in the spotlight, companies can tap into the potential of AI to provide a motivated, satisfied, and efficient workforce, thus achieving the aims and targets of the Saudi Arabian Vision 2030 of industrial excellence, and economic diversification.

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