“Enhancing banks’ HR service quality through digital transformation: Investigating the moderating role of human-AI collaboration”

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ENHANCING BANKS' HR SERVICE QUALITY THROUGH DIGITAL TRANSFORMATION: INVESTIGATING THE MODERATING ROLE OF HUMAN-AI COLLABORATION

Abstract

The study aims to investigate the effect of the digital HR transformation on the quality of HR services delivered in Saudi commercial banks and to determine whether the human-AI collaboration climate moderates the relationship. The relevance of the study is predicated on the reality that the trend of digitalizing HR processes is growing, and it is a strategic requirement that such developments find their way into the practical outcomes of services delivered to a bank's staff. The research used a quantitative cross-sectional survey to study the staff at the headquarters of ten Saudi commercial banks in Riyadh. Structural equation modeling was employed to test the study's hypothesis to verify the measurement structure and test the hypothesized structural paths. The empirical results show that the effect of digital HR transformation on the quality of HR services is positive (b = 0.487, T = 8.392, p = 0.001). Attitudes towards human-AI cooperation also play a statistically significant moderating role (b = 0.138, T = 2.142, p = 0.033). This means that the positive environment of human-AI interaction boosts the contribution of digital HR systems to the service delivery process. The results show that it is important to invest in technology and create organizational climates that make it easier for people and AI to work together. This dynamic offers practical changes that can be implemented by banking institutions to enhance the quality of HR services by aligning digital changes in the strategy.

Keywords digital HR transformation, bank service quality, human-AI collaboration climate, Saudi banking sector, Vision 2030

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INTRODUCTION

Nowadays, HR processes have progressed from paper-based to interface-based processes during recruitment, learning, performance management, and employee self-service. Banking has been introducing successive waves of technologies, and banks in Saudi Arabia operate in an environment of increased modernization needs related to national digitalization programs prioritizing data integrity, auditability, and integration throughout enterprise functions. In this environment, the quality of HR services perceived in terms of responsiveness, procedural justice, communication clarity, and day-in-day-out support remains at the core of internal output, driving trust, engagement, and commitment (Abdullah et al., 2021; Sharma et al., 2016; Zeithaml et al., 2018). While digital HR applications promise shorter cycle times, fewer errors, and greater transparency, the extent to which such benefits are realized at the employee interface is not automatic. Cloud suites, self-service portals, and AI-assisted decisions can streamline back-office tasks yet still leave front-stage service experiences uneven

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if workflows, roles, and accountability are not redesigned with the user journey in mind (Al-kharabsheh et al., 2023; Alrawahna et al., 2025).

One trend in recent organizational research has been that social contexts of tool utilization frequently prove as potent as tools themselves. Employees will be likely to regard HR services as fair and reliable as they receive proper training, can see algorithmic recommendations being made, and feel enabled to question or override, in those cases necessary, features of an environment for practical human-AI teaming (Bankins et al., 2024; Li et al., 4202). Evidence also shows complementary advantages in which rollouts concentrate on transparency, iterative exploration, and across-the-board upskilling; in these conditions, digital rollouts come to boost in-house service quality rather than merely redistributing tasks (Hemmer et al., 2023; Taslim et al., 2025). In highly regulated and compliance-intensive settings such as Saudi banking, these socio-technical conditions matter even more: service reliability and procedural justice sit alongside efficiency as non-negotiables for employees interacting with HR on pay, benefits, leave, and performance issues. Collectively, the modern practice and research can be summarized as holding a pragmatic perspective: digital HR may enhance employee-facing service delivery, yet it is only possible in the case of alignment of technology, process design, and everyday behaviors (Al-kharabsheh et al., 2023; Li et al., 2024; Krasonikolakis et al., 2020; El Saeed et al., 2025).

According to the emerging studies in the field of organizational behavior, the most effective way to introduce AI within the organization is by ensuring that its employees are sure of their capacity to use AI tools, believe in the fairness of the systems, and work in an atmosphere that facilitates human-AI complementarity (Bankins et al., 2024; Zhang et al., 2025). The benefits of digital transformation can be increased by an AI-friendly environment, which includes transparent AI systems, well-defined roles, open training, and freedom to experiment. Studies have shown that such climates enhance job enrichment and HRM innovation (Do et al., 2025; Hemmer et al., 2023; Madanchian & Taherdoost, 2025). However, the moderating effect of this climate on the relationship between digital HR transformation and HR service quality remains unexplored. By investigating this relationship, the study responds to calls for research that addresses the socio-technical conditions under which digital tools yield positive outcomes for internal HR stakeholders.

1. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Across service-based industries, hyper-speed digitalization has redefined the boundaries of how organizations internally structure work and externally control stakeholder experience. In financial organizations, digitization targeted customer-facing channels, but most enduring performance effects increasingly depend on "inside the house" reorganization of people, process, and data capabilities, especially in HRM. The new interface between digital transformation in HR and service excellence has thus become a critical research frontier in HRM, especially in highly regulated and customer-centric areas such as finance (Al-Ghalabi et al., 2024; AlNawafleh et al., 2022). Early e-HRM and HR analytics syntheses long held tech-enabled HR possibilities for reducing transaction costs, improving information quality, and aligning HR for value-plus work (Bondarouk & Brewster, 2016; Marler & Boudreau, 2017). The problem, though, isn't any more if digitalization "arrives" in HR, but how it is embedded, governed, and socially absorbed so information quality rises rather than falls (Alzghoul et al., 2023; Tawalbeh et al., 2025). That reconceptualization shifts attention from tool adoption towards system results and contingencies in hand.

This trend is being observed in the case of the financial sector of Saudi Arabia, wherein the national plans of the Vision 2030 directly relate digital government, smart services, and human-capital development to diversification and competitiveness. The plans of the national policy (like the National Transformation Plan) and sector plans spurred investments in digital infrastructure, fi-

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nance rails, and precursors of workforce upgradation where bank HR functions are and are striving to be reproduced (Asem et al., 2024; Yamin et al., 2024). Such national requirements present a paper trail in the official records and guidelines of digitization and public-service enhancement in the Vision 2030, which frames the contextualization of organizational change as part of a bigger institutional project to transition towards digitization and productivity-driven rule. A first wave of digitized HR at the organizational level existed earlier but in the simpler form of core systems (payroll, leave, and employee self-service) and simple analytics, but the most recent forms introduce AI in recruitment, performance, learning, and employee support and promise more decision quality and responsiveness (Alsalman, 2025; Dima et al., 2024; Nawaz et al., 2024). The opportunities (cost, speed, transparency) and warning signs (fragmentation, role ambiguity, user resistance) in e-HRM reviews evidence the necessity to carefully align sociotechnical instead of changing technology (Marler & Fisher, 2018; Parry & Battista, 2023; Ivchyk, 2024; Shrivastava, 2025). Synthetic lessons gained on a large scale attest that analytics and digitization are beneficial when integrated within capabilities and routines and not placed as a tool.

The more the banks go digital, the more the HR service to internal stakeholders can be used as a point of leverage in the overall service excellence. HR service quality relates to the extent to which HR delivers its services to the employees and managers in a timely, accurate, accessible, and useful manner (Uen et al., 2012). The dimensions included in SERVQUAL (responsiveness, reliability, assurance, empathy, and tangibles) have been employed in numerous studies to determine the level of workability of the HR and the degree of employee satisfaction (Parasuraman et al., 1988; Zeithaml et al., 2018). The concept is quite easy to understand: the faster HR addresses issues, the better the communication is, and the more certain that the processes are not unfair, the more the employees on the frontline will be able to concentrate on satisfying the customer and adhering to the regulations. Internal quality has improved service performance in service-related environments (Anika, 2024; de Bruin et al., 2021; Sharma et al., 2016). Banking and other service research studies have associated more positive experiences related to the HR service with employee morale, decreased friction in routine transactions, and behavioral cultures of compliance (Kim et al., 2024; Stirpe et al., 2022). The traditions of measurement are, however, split: some works rely on SERVQUAL-like scales of perceptions; others rely on instrument process measures (closed tickets, cycle times), and a third group of research combines engagement and attrition measures. The strength of perception-based measures is construct validity for "service quality" as experienced by users; their weakness is common-method bias if measured alongside outcomes from the same respondents. Conversely, process metrics provide behavioral traces but can miss quality nuances (e.g., empathy).

Digitally transformed HR embeds cloud platforms, mobile self-service, workflow automation, and analytics into recruitment, performance, learning, and employee support (Bondarouk & Brewster, 2016; Marler & Fisher, 2018; Fauziah et al., 2025). The mechanism logic is threefold. First, automation reduces latency and errors in routine transactions (e.g., leave, payroll, attestations), improving responsiveness and reliability. Second, data integration enables visibility into service performance (e.g., SLA adherence, backlog), making bottlenecks diagnosable. Third, decision-support (analytics and, increasingly, AI) enhances the fairness and timeliness of evaluations, queries, and cases, reinforcing assurance and perceived justice. Empirical work in and beyond banking supports these pathways. Global evidence shows positive associations between integrated HR platforms and employee satisfaction and lower turnover intentions (Alsalman, 2025); cross-national analyses report that digitized HR is associated with perceived service quality in knowledge-intensive environments (Parry & Battista, 2023), and meta-analytic work finds consistent positive links between e-HR practices and service outcomes (Marler & Fisher, 2018). However, these benefits are contingent on implementation quality. Poorly designed self-service, opaque decisions, or fragmented systems can produce frustration and distrust (Eprianto et al., 2022). Studies in the GCC, including Saudi Arabia, describe heterogeneous adoption and uneven capability maturity, indicating that "digital HR" is a broad label covering very different realities across institutions (Asem et al., 2024; Yamin et al., 2024; Alsalman, 2025).

Three theoretical frames organize how digital HR might influence HR service quality and why effects vary across banks. Resource-Based View (RBV) posits that sustained advantage stems from valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In HRM, AI-facilitated recruitment (e.g., better talent-signal extraction) and performance analytics can form strategic resource bundles if they are embedded in organization-specific processes and know-how (Delery & Roumpi, 2017). In tightly regulated Saudi banking, where reliability and compliance are strategic, digitally transformed HR practices that deliver consistent, auditable service act as RBV-consistent resources (Alwehabie, 2017; Mahade et al., 2025). The RBV lens also cautions that technologies alone are rarely VRIN; complementarities (governance, skills, culture) matter. Technology Acceptance Model (TAM), adoption and use are shaped by perceived usefulness and ease of use (Davis, 1989). In HR settings, employee uptake of platforms and AI-enabled tools depends on usability, trust, and workflow fit (Venkatesh et al., 2018). Empirical work in banking indicates that perceived utility of digital HR is associated with improved job performance and satisfaction (Fenech et al., 2019). According to Davis (1989), TAM contributes a micro-foundation for why "the same" technology yields divergent outcomes across units: acceptance and sustained use are not automatic. This concerns the core TAM argument and measures. Socio-Technical Systems (STS) theory emphasizes the co-optimization of social and technical subsystems (Trist & Bamforth, 2000), spotlighting design choices that align technology with human values, roles, and culture. For Saudi banks, STS points to automation and human-centeredness: workflows, role clarity, and capability building must evolve with tools. STS therefore explains why identical software can improve service quality in one bank and degrade it in another: the coupling of tech, structure, and culture differs. Thus, RBV explains why digital HR can become a strategic asset; TAM explains why users adopt or resist; and STS explains why socio-organizational design conditions the realized value. The present study integrates these lenses to analyze digital HR's effect on HR service quality and the conditions that amplify it.

The injection of AI into HR (e.g., for screening, matching, performance signals, customized learning, and conversational support) raises stakes: models can scale decision support, but value relies upon accuracy, transparency, and trust in the organization. Management and information systems research evidence reinforces that cultural and organizational binding constraints to AI success, not just technical, lie in mindset, literacy, and routines of organizational change (Fountaine et al., 2019). One rapidly growing literature investigates human trust in AI, an essential condition for long-term use and impact. Syntheses show trust relies upon perceived transparency, reliability, and fit between the capability and capacity of AI, and in part upon prior experience of people and norms of the organization, too (Glikson & Woolley, 2020). Concisely, people will collaborate better with AI if they understand it, if it is accurate in the pertinent domain, and if the surrounding culture approves human-AI teaming. At the workforce level, evidence on STARA (smart technology, AI, robots, algorithms) research shows employee awareness of automation can cause anxiety, perceptions of insecure jobs, and resistance, if capability-building and transparent role design do not counterbalance (Brougham & Haar, 2018, 2020). These findings particularly have significance for HR use-cases involving identity-relevant decisions (e.g., assessing performance), in which perceived fairness is critical. Transposing these lessons to HR service quality signifies AI can lift responsiveness (e.g., chatbots providing policy information), reliability (e.g., payroll anomalous detection), and assurance (e.g., standardized criteria for decisions) if employee experience of AI as agency-augmenting, not undermining, dominates. Organizations that invest in AI literacy, provide explanations for AI-supported decisions, and solicit user feedback are more likely to see HR service quality gains, while "tech-first" rollouts risk eroding trust. This mechanism logic aligns with widely cited managerial evidence and academic reviews (Kalff & Simbeck, 2025; Pan et al., 2025).

The human-AI collaboration climate refers to employees' shared perceptions that AI-based systems are deployed fairly, transparently, and with adequate support, i.e., that the organization treats human-AI teaming as a partnership. In high-quality climates, employees are trained to interpret AI outputs, escalation norms are clear, and leaders frame AI as a tool to enhance, not replace, profes-

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sional judgment (Bankins et al., 2024; Brougham & Haar, 2018; Fountaine et al., 2019). In low-quality climates, opacity and "automation bias" erode trust; employees bypass systems or engage in surface compliance, neutralizing potential benefits (Dwivedi et al., 2021; Gao & Zamanpour, 2024; Madanchian & Taherdoost, 2025). Empirical studies, both in HR analytics and banking, have begun to document this moderating dynamic, showing that the link between analytics/AI and decision quality is stronger where collaborative climates exist (Mahade et al., 2025; Madhuri & Kumar, 2025) and where trust in AI is actively cultivated (Agustiawan, 2024). From a theory standpoint, the moderation is intuitive: RBV says the resource (AI and digital HR) yields value when it is combined with complementary assets (skills, governance, norms); TAM says usefulness and ease of use raise adoption; STS says socio-technical alignment is required. Human-AI collaboration climate summarizes these complementarities into a measurable, company-wide condition that would systematically amplify the impact of digital HR on HR service quality in Saudi banks.

Notably, little in-context evidence is available as yet for how the digitalization of HR takes shape in the internal HR service quality of Saudi banks, and under what organizational settings. The human-AI cooperation climate has been accorded little direct, empirical focus in this regard. Existing Saudi or GCC studies often conflate adoption with impact, leaving the mechanism logic underspecified (Asem et al., 2024; Alsalman, 2025; Yamin et al., 2024). Across the literature, a coherent pattern emerges: digital HR transformation is consistently associated with internal service improvements when it is embedded in complementary organizational capabilities and norms; absent those complements, promised gains often fail to materialize. Moreover, as AI becomes integral to HR processes, the climate surrounding human–AI collaboration increasingly determines whether employees experience digital HR as fair, transparent, and genuinely helpful. Nevertheless, there is limited research detailing these relationships in the Saudi banking field.

To fill this gap, this paper will explore whether and how the digital HR transformation can improve the quality of HR services in Saudi banks and will test the hypothesis that the human-AI collaboration climate can moderate the connection between the two.

H1: Digital HR transformation has a significant positive impact on HR service quality in Saudi banks.

H2: The human-AI collaboration climate moderates the relationship between digital HR transformation and HR service quality.

2. METHODOLOGY

The study was based on a quantitative method, a cross-sectional survey study, to test hypothesized relationships between latent constructs (digital HR transformation, HR service quality, moderating role of the human-AI collaboration climate) using structural equation modeling (SEM). The cross-sectional survey is highly appropriate in such a situation because it helps to have a snapshot of perceptions in a specific population, and with proper sampling and testing of the model, it is possible to generalize this kind of survey. SEM can be used to measure both measurement and structural paths among latent variables concurrently. The target population will include employees located at the Riyadh headquarters of ten Saudi commercial banks (Saudi National Bank (SNB), Al Rajhi Bank, Riyad Bank, Saudi Awwal Bank (SAB), Banque Saudi Fransi (BSF), Arab National Bank (ANB), The Saudi Investment Bank (SAIB), Alinma Bank, Bank AlBilad, and Bank AlJazira) that have a direct relationship with the HR services. Inclusion included (a) HR service channel providers (e.g., HR operations, HR shared services, talent management, and HRIS/IT supporting HR platforms) and (b) those employees who engage regularly with the HR service channels as part of their work (e.g., line managers and unit leads at the HQ that make HR requests, approvals or cases). The banking industry was chosen due to its importance in the vision of 2030 and the rapid course of digitalization within the framework of the national programs, which puts the focus on digital transactions and the modernization of financial services. The 500 structured questionnaires were also sent electronically through official bank email networks and professional HR in forums within a period of four weeks, with two reminders sent towards the field period. Following data cleaning and filtering out of incomplete responses, 274 valid cases were left to analyze (54.8% response rate). This is a large sample size that exceeds the normal requirements of Structural Equation Modeling (SEM) in survey research, and therefore, it is appropriate to have high measurement and structural modeling.

The survey was structured in three multi-item reflective constructs rated on 5-point Likert scales (1 strongly disagree, 5 strongly agree). The survey was pre-tested by five domain specialists on e-HR and organizational behavior to verify that it was valid and applicable to the Saudi Arabian context. There was also a pilot survey of 30 individuals that tested how clear the items were, and this did not produce any major linguistic changes. Data were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4.0. The reason why this technique was selected is that it is effective in predictive modeling when the sample size is not large, and the latent factors are complex (Hair et al., 2021). The PLS-SEM allows us to assess the measurement model (the degree of reliability and validity of the constructs) and the structural model (the hypothesized relationships) simultaneously.

Table 1. Sample characteristics

Variable	Category	n	%
Gender	Male	181	66.1%
	Female	93	33.9%
Birth cohort	Born after 2000	22	8.0%
	1980–2000	192	70.1%
	1965–1979	55	20.1%
	Born before 1965	5	1.8%
Educational level	Bachelor's degree	159	58.0%
	Master degree	99	36.2%
	Doctorate degree	16	5.8%
Years in service (workforce)	< 4 years	33	12.0%
	5-9 years	104	38.0%
	≥ 10 years	137	50.0%
Job function	Managers	82	٩.٩٢%
	Supervisors	67	٤.٤٢%
	employees	101	9%.٦٣
	Data analysts	24	٨.٨%
Total	–	274	**100%**

The sample population (N = 274) represents a male-dominant managerial workforce (66.1%), with a little more than a third of it (33.9%) of the female gender. Despite the gender ratio, the female presence is significant in a panel of bank leaders and serves as a tool for decreasing the risk of single-point-of-view bias in the outlooks of digital HR, AI enablement, and service. The age profile suggested by the cohort of birth constitutes the mid-career profiles: 70.1% were born in the years 1980 to 2000, and 20.1% were born in 1965 to 1979. The number of post-2000 entrants is only 8.0% and the number of pre-1965 entrants is 1.8%. This concentration of experienced age groups will be suitable for research that evaluates the enterprise systems and collaboration with AI topics, which usually require familiarity with the organization, ownership of processes, and may have been exposed to transformation programs. The educational system is well-educated: 58.0% have bachelor's degrees, 36.2% master's, and 5.8% are doctors. This is an HR, IT, and HR service delivery management profile that aligns with role expectations and indicates that respondents have the conceptual and analytical background to evaluate digital HR systems and AI integration with credibility.

The sample workforce is skewed towards seniors: 50.0% have 10 years of experience, 38.0% fall within the 5-9-year bracket, and 12.0% have less than 4 years of experience. This distribution is beneficial to external validity in banks: the respondents will, most likely, have encountered several technology cycles (e.g., HRIS upgrades, core-system changes, early AI pilots) and are able to differentiate short-term tools and long-term capabilities that can lead to positive effects on service quality. The sample represents an equal cross-section of job functions at the Riyadh headquarters. Managers (29.9%) and supervisors (24.4%) come next, and data analysts are also a smaller but significant group (8.8%). This combination includes both operational and strategic perspectives, which are significant for assessing digital HR change and perceived HR service quality. Even though data analysts are a smaller group, their perspective on HRIS and AI-powered processes provides a layer of understanding. Simultaneously, the presence of data analysts would be beneficial to have an additional technical voice; their opinions could balance the confidence or distrust towards AI-enabled processes, model results, and the quality of measurements. Overall, the dissemination enhances both the validity and reliability of the study's findings in the sampled banks.

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3. RESULTS

The study used Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 to check the expected connections between digital HR transformation (DHR), HR service quality (HRQ), and how human-AI collaboration climate (HAICC) plays a role in this. We collectively subjected the entire set of 274 responses to analysis. We evaluated the measurement model and structural model based on predesignated reliability, validity, and model fit. PLS-SEM was utilized as the primary analysis tool to test both reliability and validity of the measurement model, as well as confirmation of the theorized relationships between the concepts. Various validity and reliability tests were run on the measurement model to establish its strength. Those included Cronbach's alpha values, Average Variance Extracted (AVE), and CR. All of them establish the fact that the scales for measuring items are convergent, consistent, and reliable. Table 1 presents all the psychometric attributes of each of the concepts under inquiry.

Table 2 presents the output of measurement model testing, here item loadings, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha of the three constructs: Digital HR Transformation, HR Service Quality, and Human-AI Collaboration Climate. All these indicators kept during the analysis demonstrated strong standard loadings above the commonly recommended 0.70 (Hair et al., 2021), reflecting strong item reliability. Of specific interest was loading for variables for the construct Digital HR Transformation, 0.767 to 0.889. This factor indicates the extent to which all the features of digital transformation (like recruitment based on AI,

Table 2. Items loading, reliability, and convergent validity of the variables

Item	Item Loading	AVE	CR	Cronbach's
Digital HR Transformation				
Our organization uses digital platforms for managing the recruitment and selection process	0.847	0.59	0.91	0.81
Performance evaluations are conducted or supported using digital tools	0.811			
HR data is stored and managed using cloud-based or centralized systems	0.874			
Employees have access to self-service HR portals for tasks such as leave requests, salary slips, or training registration	0.767			
Our HR system is integrated with other business functions such as payroll, finance, and IT	0.889			
The HR department continuously updates its digital tools to meet changing workforce needs	0.792			
Training is regularly provided to HR staff to improve their use of digital HR tools	0.825			
HR Service Quality				
HR staff are knowledgeable and competent in their roles	0.861	0.67	0.94	0.92
HR issues are resolved in a timely and efficient manner	0.848			
The communication from HR is clear, consistent, and informative	0.821			
HR services are easy to access through both digital and in-person channels	0.796			
I receive individual attention when dealing with the HR department	0.763			
HR policies and procedures are applied fairly to all employees	0.817			
I trust the HR department to handle my personal and professional matters with confidentiality	0.883			
I am satisfied with the overall service quality provided by the HR team	0.891			
The HR department is proactive in identifying and addressing employee needs	0.853			
HR–AI Collaboration Climate				
The organization encourages HR professionals to collaborate with AI-based systems	0.811	0.61	0.92	0.90
AI systems are seen as supportive tools, not replacements for human roles	0.783			
HR employees are trained to work effectively with AI technologies	0.726			
The organization provides clear guidance on how decisions should be made using both human judgment and AI input	0.715			
Feedback from HR employees is used to improve AI tools	0.731			
There is a shared belief in the fairness of AI systems used in HR functions (e.g., resume screening)	0.836			
Our AI tools are transparent and explainable in terms of how they operate or make decisions	Deleted			
Managers encourage an open discussion on the strengths and limitations of AI in HR	0.842			
The collaboration between AI and human professionals in HR improves service effectiveness.	0.868			

tracking the performance, integrating the HR functions, and other company functions) contribute to workers' perception of the digitization of HR as a whole. The average variance extracted (AVE) for the construct index came in at 0.59, which was marginally higher than the satisfactory level of 0.50 for adequate convergent validity (Hair et al., 2021). Its internal consistency was also ascertained from its composite reliability (CR = 0.91) and Cronbach's alpha (α = 0.81).

Regarding the construct of the HR service quality, item loading was equally high with scores between 0.763 and 0.891. These items encompassed key service dimensions, which included the responsiveness of HR, its accessibility, and its fairness. A high AVE of 0.67 and CR with a high value of 0.94 and Cronbach's alpha of 0.92 confirm the fact that this construct measures a coherent and reliable latent dimension. These measurements show that workers judge the quality of HR service provision not only through functionality provision but also interpersonal sensitivity and trust, especially in sensitive areas. The Human-AI Collaboration Climate construct was first developed with ten items; however, one of those items, which concerned AI transparency, was dropped as a result of below-sub-threshold loading. The retained indicators showed loading values of 0.715 to 0.868, and the construct retained good reliability and validity (AVE = 0.61, CR = 0.92, a = 0.90). The result confirms the perception of fairness, role complementarity, and managerial encouragement as the determinants of the climate of larger-scale human-AI cooperation. The moderate to high loadings indicate the diverse but unified aspects that characterize a supportive AI-enabled work environment.

The results of the Fornell-Larcker criterion to evaluate the discriminant validity of the three latent constructs, which are Digital HR Transformation, HR Service Quality, and Human-AI Collaboration Climate, are presented in Table 3. The Fornell-Larcker principle states that the square root of the average variance extracted (AVE) of each construct (presented along the diagonal) needs to be greater than its correlations with other constructs in the model (Fornell & Larcker, 1981). The diagonal values of all three constructs satisfy this requirement in this analysis. In particular, the square root of the AVE of Digital HR Transformation is 0.770, higher than that of the correlations between it and HR Service Quality (0.643) and Human-AI Collaboration Climate (0.597). Similarly, the square root of AVE of HR Service Quality has the value of 0.823, which is well above the shared value of the construct with the other constructs. Lastly, the Human-AI Collaboration Climate construct has a value of 0.781 on a diagonal, which is higher than its correlation with Digital HR Transformation and HR Service Quality. These findings confirm the idea that both constructions are measures of different conceptual areas, despite moderate correlations between them. Theoretically, this corresponds to the idea that digital HR tools, HR service delivery, and AI-inspired collaboration climates are associated phenomena that are functionally different. Discriminant validity is confirmed and provides a strong factor that validates the measurement model and allows the interpretation of future structural path analyses to be made without fear of conceptual overlap.

Table 4 presents the results of the structural model analysis, including the path coefficients, t-values,

Table 3. Discriminant validity by HTMT

Construct	Digital HR Transformation	HR Service Quality	Human-AI Collaboration Climate
Digital HR Transformation	0.770	–	–
HR Service Quality	0.643	0.823	–
Human-AI Collaboration Climate	0.597	0.683	0.781

Table 4. Hypothesis testing results

No.	Hypotheses	Path Coefficient	T-Value	P-Value	Confidence Interval		Decision
					95% LL	95% UL	
1	DHR → HRQ	0.487	8.392	0.001	0.375	0.602	Supported
2	DHR × HAICC → HRQ	0.138	2.142	0.033	0.013	0.265	Supported

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p-values, and 95% bias-corrected confidence interval obtained after bootstrapping on 5,000 subsamples. Both the relationships hypothesized turned out to be significant. In the case of Hypothesis 1, the standardized coefficient between digital HR transformation and HR service quality was 0.487, and significant at the $p < 0.001$ level. The t-value of 8.392 is high, which explains a strong empirical support of the direct effect, and the stability of the estimate is verified by the confidence interval [0.375, 0.602]. This finding supports the view that digital HR systems make a significant contribution to enhancing the quality of perceived HR services among employees. Such gains can be the result of the better availability of HR services, automation of administrative functions, and timely handling of HR-related requests.

Hypothesis 2: The hypothesis tested the existence of the moderating effect of the human-AI collaboration climate between DHR and HRQ. The interaction term (DHR x HAICC) also had a statistically significant value, with the path coefficient of 0.138, and a p-value of 0.033. The confidence interval [0.013, 0.265] and t-value of 2.142 indicate a small yet significant moderating effect. This means that the advantages of the digital HR transformation on the service quality are enhanced when the organizational climate encourages collaborative interaction with AI systems. This result demonstrates the significance of technological investment, as well as cultural preparedness and employee buy-in to achieve all the potential benefits of digital HR initiatives. Collectively, these findings provide empirical evidence of the suggested model and underline that the activities of digital transformation should be facilitated by organizational interventions that induce human-AI synergy. The relevance of direct and interaction effects supplements the multi-dimensional quality service, resulting in a digitally changing HR landscape.

4. DISCUSSION

The study endeavored to investigate the impact of digital HR transformation on HR service quality for Saudi Arabian banking institutions and also test the moderating function of the human–AI collaboration climate. The outputs yield theory contribution as well as practice insight for digital HRM and service administration for rapidly rising markets during rapid-track digital transformations. Primarily, a favorable DHR–service quality relationship signifies more than fast, signifies technology-enabled HR capabilities as extensionally valued resources get integrated into extended core HR processes. This underpins the Resource-Based View, forecasting long-run benefits, if instead of bolt-on tools, organizations develop VRIN capabilities (Barney, 1991). In banks, where auditability, compliance, and cycle-time matter most, integrated suites, tying payroll, learning, and performance management, believably boost reliability and transparency, two facets of SERVQUAL significantly related to perceived service quality (Parasuraman et al., 1988). Earlier e-HRM overviews correspondingly report digital HR to boost responsiveness and consistency if adoption becomes enterprise-wide and process-centric (Ivchyk, 2024; Marler & Fisher, 2018; Shrivastava, 2025). Generally, study evidence and overviews signal banks to reap the service-quality advantage of DHR if they treat HR-technology as a capability platform, instead of a set of standalone apps.

Second, HAICC's strong moderating role indicates a socio-technical boundary condition: the same tools produce uneven benefits depending on how people are incentivized to cooperate with them. Normalized human-AI teaming, clear task boundaries, training in AI-enabled decisions, and channels to criticize model outputs appear to unlock more value in DHR's terms in terms of service quality. This fits richer AI adoption research with findability, trustworthiness, and end-user engagement having an impact on value realization, not just accuracy measures (Dwivedi et al., 2021). In practice, Saudi banks that pair platform deployments with formal AI enablement (role-based training, feedback, and governance) should see larger value increments in responsiveness and assurance, the "softer" characteristics workers experience when dealing with HR. Where psychological security runs low, or where AI remains black-box, there's under-utilization after large tech investments.

Third, Saudi banking combines high digital ambition and hierarchical decision norms. In-group deference to authority and personal-problemsolving biases can slow transitions from human-only workflows to human-AI teaming without implementation participation. The study finding that HAICC conditions the DHR-quality relationship implies programs of transformation have to be phased: launch small sets of high-certainty use cases (e.g., policy guidance chat, leave management), invest in "explain the AI" practices, and build sponsorship at multiple hierarchy layers, not only at the summit. This phasing turns cultural headwinds into learning advantages and reduces the risk that people perceive DHR as depersonalization, not service improvement. Finally, this study contributes by reconciling resource-based and socio-technical perspectives. DHR appears to supply technical tract (capability building), and HAICC supplies cultural tract (capability enactment). Modeling both helps to narrate why some digital programs stall despite strong business cases. This also addresses exhortations for richer, interaction-focal models of technology adoption specifying under what circumstances and in whose life digital investments pay (Dwivedi et al., 2021). Two areas of research follow for academics: (a) unpack which dimensions of HAICC (e.g., training sufficiency vs transparency in decisions) most forcefully multiply DHR's benefits, and (b) put different explanations (e.g., digital direction of leaders) to test to eliminate governance or shared-method confounds. Practitioners learn this lesson: spend not only in platforms, but in those human systems making platforms usable, trustworthy, and worth employing.

CONCLUSION

This study investigates whether the core HR's digital transformation raises the level of HR service quality in Saudi Arabian banks and whether such an impact relies on an enabling human-AI collaboration environment. The study identifies that core HR functions' digitization goes side by side with significantly higher service quality witnessed through streamlined end-to-end transaction processing, faster and more frequent responses by staff, and clearer two-way communications. These are efficiency plus perceptual gains: people have more trust in HR decisions, are more knowledgeable about policies and entitlements, and feel fewer mistakes in servicing. Notably, the units where human-AI teaming is fostered see the advantages much higher up the line, where individuals get experience working with AI; they can review advice suggested by the algorithm and view technology as both just and harmless, and culture and ability must remain inseparable so that digital can bring about service brilliance. The bank must also think of digital HR as an end-to-end solution and not a collection of apps. Once the foundation of recruitment, payroll, performance, learning, and compliance is combined on one base, the reliability increases, the turnaround time decreases, and transparency becomes embedded in every interaction. True value, however, relies on creating a supportive atmosphere for the engagement between humans and AI, which includes tailored training, clear explanations of tool functionality, and governance-over-participation to help workers feel confident in utilizing and questioning the AI's output. Even the latest systems do not give half their potential without these cornerstones. The concept of technology implementation in the context of Vision 2030 should remain in step with change leadership. That means there should be a high degree of executive sponsorship and right-enabled positions, as well as frequent feedback mechanisms to raise issues early and maintain the pace at the right level. Technology-enabled HR, so characterized, is not an IT upgrade but a capabilities-oriented profession, and the payoff of the service level comes at the point that technology, culture, and everyday practice get into synch.

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