

Article

The Mediating Role of Internal Marketing in the Relationship Between Artificial Intelligence Applications and Quality of Work Life: A Field Study on Service Ministries in Saudi Arabia

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Abstract

Purpose: This study investigates the mediating role of internal marketing (IM) in the relationship between artificial intelligence (AI) applications and quality of work life (QWL). **Methodology:** A quantitative cross-sectional research design was employed. Data were collected via self-administered questionnaires from a sample of 418 employees across service ministries in Saudi Arabia and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) as the analytical instrument. **Findings:** The results reveal that the direct association between AI applications and QWL was not statistically significant. However, a significant indirect relationship was established, indicating that the effect operates entirely through IM. Specifically, AI applications are positively associated with IM practices, which in turn strongly predict higher QWL in the tested model. **Originality/Contributions:** The study advances current literature by empirically validating IM as the critical organizational mechanism required to translate AI deployment into employee well-being within public-sector institutions. **Practical Implications:** Decision-makers must couple AI adoption with targeted IM strategies—such as continuous training, job empowerment, and effective internal communication—to ensure a sustainable, human-centered digital transformation.

Keywords: artificial intelligence; quality of work life; internal marketing; sustainable development; social sustainability human-centered digital transformation; employee well-being; public sector; Saudi Arabia

1. Introduction

Contemporary work environments are undergoing profound transformations due to the Fourth Industrial Revolution and artificial intelligence (AI) applications. These technologies have become pivotal factors reshaping the nature of work and directly affecting employees' quality of work life (QWL), necessitating a reconsideration of managerial strategies to balance operational gains with employee well-being [1–3]. This transformation is particularly significant in Saudi Arabia, where AI is a core pillar of Saudi Vision 2030. With 66 out of 96 strategic objectives depending on AI and digital technologies [4,5], government service ministries must effectively integrate these tools to enhance public service efficiency.

Theoretically, aligned with Socio-Technical Systems Theory and Industry 5.0, technology should serve human needs rather than marginalize them [1]. Empirically, AI applications can positively impact QWL by reducing administrative burdens and enhancing performance expectancy [2,3,6]. However, implementing AI without considering human



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factors risks adverse outcomes, such as reduced job autonomy, social isolation, and skill erosion, particularly under algorithmic management [2,7].

To mitigate these risks, internal marketing (IM) emerges as a vital managerial mechanism. By treating employees as internal customers, IM practices—such as effective communication, training, empowerment, and fair rewards—foster a supportive culture [8–11]. IM positively influences job satisfaction and organizational citizenship behavior, including within the Saudi context [10,12]. Concurrently, QWL reflects employees' well-being, encompassing job security, work–life balance, and organizational justice [13,14]. Elevating QWL is a central priority of the Saudi Vision 2030 Quality of Life Program, driving government institutions to adopt practices that support employee well-being [15,16].

Despite growing interest, a significant research gap persists regarding the mechanisms through which AI's positive impact on QWL can be maximized. While existing studies separately examine the direct relationship between AI and QWL [17,18] or IM and job satisfaction [10,11], integrative models linking these three variables remain scarce, especially in the Arab public sector.

This study addresses this gap by investigating the mediating role of IM in the relationship between AI applications and QWL within Saudi service ministries. This aligns with contemporary sustainability scholarship, viewing human-centered digital transformation as integral to sustainable organizational development [19]. Consequently, this study addresses the following research questions (RQs):

RQ1: What are the direct effects of AI applications on IM and QWL among employees in Saudi service ministries?

RQ2: To what extent does IM mediate the relationship between AI applications and QWL?

Aligned with these questions, the research objectives (ROs) are:

RO1: To examine the direct impact of AI applications on IM and QWL.

RO2: To empirically test and validate the mediating role of IM in the relationship between AI applications and QWL.

2. Theoretical Framework and Previous Studies

2.1. Artificial Intelligence Applications in the Work Environment

AI represents one of the most prominent technological developments witnessed in the modern era, having moved from merely a theoretical concept to a tangible reality affecting various aspects of human life. AI is defined as the ability to develop computer systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, planning, problem-solving, and natural language understanding [2]. In the context of contemporary work environments, AI applications encompass a wide spectrum of tools and systems aimed at improving operational efficiency and enhancing decision-making quality.

From a historical perspective, the roots of Socio-Technical Systems Theory (STST) date back to the 1950s, when researchers at the Tavistock Institute in Britain sought to find a balance between technical requirements and the social needs of workers. This theory emphasized that the success of technical systems depends on their integration with the social system of the organization and that technology should be designed in ways that support employee well-being rather than marginalize the human element [1]. In the context of the present study, STST provides the structural explanation for why AI applications, as elements of the technical subsystem, cannot independently improve QWL unless aligned with organizational practices within the social subsystem, operationalized here through IM practices. Internal communication, empowerment, training, and reward systems function as organizational mechanisms through which AI capabilities are translated into employee outcomes. Social Exchange Theory [20] complements this perspective by

explaining the motivational mechanism underlying this relationship. When organizations invest in AI-enabled internal marketing practices, employees perceive these investments as signals of organizational support and reciprocate through enhanced well-being and commitment [21]. Finally, the Industry 5.0 perspective provides the broader normative orientation by emphasizing human-centered and sustainable technological transformation, where employee well-being represents a central outcome of digital transformation processes [19]. Together, these perspectives provide a coherent theoretical foundation for explaining how AI applications influence QWL through internal marketing practices.

Together, these frameworks form a coherent architecture. While STST and SET serve as the formal organizational theories explaining the structural and motivational mechanisms of mediation, respectively, Industry 5.0 acts as the overarching normative philosophy. It is not an explanatory theory, but rather a paradigm that dictates the ethical priority of human-centric technological transformation. AI applications in service organizations are diverse and vary according to the nature of services provided and the needs of employees and customers. These applications range from automating routine administrative tasks to providing personalized recommendations, offering immersive training environments, supporting continuous professional development, and analyzing internal communication patterns among employees. Studies have shown that such applications contribute to reducing administrative workloads, improving process efficiency, enhancing employee satisfaction, and providing valuable insights into employees' needs and required areas of improvement [2,3,6,18,22].

Contemporary literature indicates that AI applications possess the ability to produce varying effects on the work environment, which can be positive or negative depending on the method of design and implementation. On the positive side, these applications contribute to improving operational efficiency, reducing human errors, saving time and resources, and enabling employees to focus on creative and strategic tasks [2,3]. However, some studies have warned of the potential risks of these technologies, such as loss of job autonomy, anxiety about job security, social isolation, and erosion of human skills due to excessive dependence on automation [7].

In this context, Nurski and Hoffmann's [7] study emphasized that the impact of AI on job quality depends significantly on how it is used; when used as an augmentation tool, it enhances employees' capabilities and improves their work quality, while when used in a directive manner, it may lead to reducing their autonomy and increasing psychological pressures. This variation underscores the importance of having clear organizational strategies that ensure optimal employment of AI applications to serve the interests of both employees and the organization.

2.2. *Quality of Work Life*

The concept of QWL is a composite concept that reflects the level of satisfaction and well-being that employees feel in their work environment. This concept has evolved over time, initially focusing on material aspects such as wages and physical working conditions, then expanding to include psychological, social, and organizational dimensions. Manea [13] defines QWL as a set of practices and procedures implemented by the organization through providing a safe and healthy work environment, achieving fairness in salaries and rewards, and meeting the psychological and social needs of employees.

QWL encompasses several main dimensions, including job security and stability, a safe and healthy work environment, work-life balance, opportunities for growth and professional development, organizational justice, participation in decision-making, and positive social relationships with colleagues and supervisors [13,14]. Studies have proven that improving QWL is positively associated with many desired organizational outcomes,

such as job performance, organizational commitment, organizational citizenship behavior, and reduced rates of absenteeism and turnover [10].

While QWL is a composite construct, not all of its dimensions are equally susceptible to the influence of AI applications and IM practices. Theoretically, three QWL dimensions constitute the most proximate targets of AI-enabled organizational change. First, workload and demand reduction: AI applications that automate routine and administrative tasks directly reduce cognitive and temporal demands on employees, thereby improving their perceived balance between work requirements and personal life [3,7]. This dimension of QWL is the most direct and immediate recipient of AI's functional benefits, operating through what Bakker and Demerouti [23] conceptualize as a reduction in job demands. Second, skill utilization and professional development: AI tools that function as cognitive augmentation systems—rather than substitutes—enable employees to engage in higher-order, value-added tasks, thereby enriching their perception of skill use and growth opportunity [7]. This dimension is particularly sensitive to how AI is deployed: augmentative use enriches skill utilization, while directive or algorithmic management use may erode it. Third, perceived organizational justice: when AI systems are employed in performance monitoring, task allocation, or reward determination, employees' perceptions of procedural and distributive fairness are directly implicated [14]. Transparent and equitable AI-assisted decision-making can reinforce justice perceptions, while opaque algorithmic management risks undermining them.

It is equally important to theorize which QWL dimensions are most sensitive to IM practices as the mediating mechanism. IM's four operationalized dimensions—internal communication, training and development, job empowerment, and reward systems—map onto specific QWL domains in theoretically predictable ways. Internal communication practices directly target employees' participation and sense of inclusion, which are foundational to the participation-in-decision-making dimension of QWL. Training and development practices directly address professional growth opportunities. Job empowerment practices enhance autonomy and perceived control over work, which is a central determinant of QWL in the socio-technical literature [1]. Reward systems, by operationalizing organizational justice in its distributive and procedural forms, address the fairness dimension of QWL. This dimensional alignment between IM practices and QWL components provides a theoretically grounded basis for expecting full rather than partial mediation: because IM comprehensively addresses the QWL dimensions most activated by AI deployment, the social mechanism is theoretically sufficient to carry the full effect.

QWL is affected by a complex set of individual, organizational, and environmental factors. At the individual level, demographic characteristics such as age, gender, and experience shape employees' perceptions of their QWL, where Meharunisa et al. [18] study in the Saudi context showed that the impact of AI applications on work–life balance differs according to the demographic characteristics of female employees, with experience and age serving as moderating factors in this relationship. At the organizational level, managerial practices and organizational climate play a pivotal role, as Al-Balawi and Dahinen's [14] study on public sector employees in Medina confirmed that organizational justice in its three dimensions—distributive, procedural, and interactional—has a statistically significant effect on QWL, where a fair organizational climate contributes to increasing workers' sense of belonging and job satisfaction.

QWL occupies a prominent position within the priorities of Saudi Vision 2030, where the Quality of Life Program aims to improve the lifestyle of individuals and families by enhancing infrastructure, providing better options for entertainment and culture, improving public services, and ensuring equal opportunities for all segments of society [15]. In the work environment specifically, Saudi government institutions seek to apply best global

practices in human resource management to ensure employee well-being and enable them to achieve the required balance between professional and personal life. Al-Ahmadi's [16] study on King Saud University indicated that the level of quality of life for students and employees is closely linked to the level of technical and educational services provided, finding that the social interactive aspect ranked highest while the educational and technical aspect ranked lowest, suggesting significant opportunities for improving QWL through investment in technical infrastructure and AI applications.

2.3. Internal Marketing

IM represents a managerial philosophy that treats employees as "internal customers" of the organization and seeks to design jobs and the organizational environment in a way that meets their needs and motivates them to deliver the best possible performance. This concept emerged in the late 1970s as a natural extension of the external marketing concept, as researchers realized that organizations' success in serving their external customers first requires ensuring the satisfaction and loyalty of internal customers [8,9].

IM research has gone through four main evolutionary stages, according to the comprehensive systematic review conducted by Qiu et al. [9]: the Emergence phase, which witnessed the birth of the concept and its initial applications in the service sector; the Establishment phase, characterized by the development of theoretical models; the Explosion phase, which witnessed significant expansion in empirical studies across various sectors and cultural contexts; and finally, the Ennui phase, characterized by a relative slowdown in research production and the emergence of criticisms about theoretical fragmentation and weak practical application.

The practices falling under IM are numerous, including effective internal communication, continuous training and development, job empowerment, fair reward and incentive systems, attention to the internal work environment, and supportive leadership [10,11]. Empirical studies have shown that these practices positively affect many attitudinal and behavioral outcomes of employees. Muramalla's [11] study on the Indian banking sector found that internal communication and employee rewards were among the most influential IM factors on job satisfaction. In the Saudi context, Al-Khudairi's [10] study on King Saud University employees confirmed a strong positive relationship between IM practices and organizational citizenship behavior, with motivation being the most influential factor, followed by internal communication.

Recent literature indicates that IM plays an important mediating role in relationships between different organizational variables. Ahmed et al. [8] proposed a theoretical model showing that organizational competencies mediate the relationship between the IM mix and business performance. Awad et al. [24] study in the tourism and hotel sector found that IM works as a moderator enhancing the relationship between organizational trust and job engagement, while Al-Khudairi's [10] study showed that job commitment plays a partial mediating role between IM and human resource ethics.

With the rapid development of AI technologies and digital transformation, researchers have begun exploring how to integrate these technologies with IM strategies. Qiu et al. [9] pointed to the necessity of using big data analytics and AI to understand employee behavior and needs more deeply, enabling organizations to customize IM practices according to individual employee needs. Panwar et al. [25] study provided empirical evidence on the importance of integrating AI-driven marketing forecasting with employee retention strategies, finding that this integration enhances organizational financial growth while raising employee morale when combined with supportive human resource strategies [25].

Relationships between Study Variables and Previous Studies.

2.4. *The Relationship Between AI Applications and QWL*

Current literature reveals a broad consensus that AI applications hold significant potential to enhance QWL, primarily by reducing routine workloads and augmenting decision-making efficiency [3,17]. However, a critical synthesis of empirical evidence highlights notable contradictions depending on the deployment strategy. On the one hand, studies examining AI as supportive and augmentative tools report consistent agreements on positive outcomes, such as enhanced work–life balance, empowerment, and professional growth in educational settings [18,26]. On the other hand, a contrasting body of literature warns that when AI is utilized directly for algorithmic management, it contradicts these positive trends by significantly eroding job autonomy, skill utilization, and increasing psychological pressure [7]. This critical divergence indicates that the AI-QWL relationship is not deterministic. Instead of technology independently driving well-being, these contradictory outcomes underscore the necessity of intervening organizational mechanisms—justifying the examination of IM as a crucial mediator.

2.5. *The Relationship Between AI Applications and Internal Marketing*

Despite the limited studies that have addressed the direct relationship between AI applications and internal marketing, there is growing evidence of a close connection between these two variables. Panwar et al. [25] study indicated that integrating AI-driven marketing forecasting with employee retention strategies enhances organizational financial growth, where results showed a positive and direct impact of AI-driven marketing forecasting on employee satisfaction ($\beta = 0.421$), suggesting that using AI in improving IM processes can contribute to enhancing employee satisfaction and commitment.

Qiu et al. [9] emphasized the necessity of transitioning to using big data analytics and AI as part of IM capabilities, transforming IM into a dynamic capability that enables the organization to quickly adapt to changes in employees' needs and expectations. Silva-Atencio's [22] study further indicated a positive perception among human resource experts of the role of AI and big data in improving professional competencies such as internal communication and motivation, provided there are clear organizational standards that ensure the ethical and effective use of these technologies.

Synthesizing this evidence, the relationship between AI applications and QWL is best understood not as a single undifferentiated effect but as a set of dimension-specific pathways operating through distinct mechanisms. The demand-reduction mechanism operates primarily on the workload and work–life balance dimensions of QWL: by automating repetitive administrative tasks, AI reduces the quantity and cognitive intensity of demands placed on employees [3,23].

The skill-augmentation mechanism operates on the professional development and skill-use dimensions: AI tools that extend employees' analytical and decision-making capabilities create conditions for deeper task engagement and perceived competency growth [7]. The justice-signaling mechanism operates on the organizational justice dimension: AI-assisted transparency in performance evaluation and reward allocation can reinforce employees' perceptions of procedural and distributive fairness [14]. Critically, however, none of these mechanisms operates independently of organizational context. The demand-reduction mechanism requires organizational recognition of freed-up time as a resource for development rather than simply an opportunity for increased task load. The skill-augmentation mechanism requires training infrastructure that helps employees engage productively with AI tools. The justice-signaling mechanism requires clear and consistent communication about how AI-generated data inform managerial decisions. This is precisely why IM—encompassing communication, training, empowerment, and

rewards—is theorized as the necessary organizational mechanism through which AI’s dimension-specific effects on QWL are activated and sustained.

2.6. *The Relationship Between IM and QWL*

The relationship between IM and QWL represents one of the main themes in contemporary human resource management literature, where many empirical studies have proven a strong positive relationship between IM practices and QWL. Muramalla’s [11] study found that IM practices, especially internal communication and employee rewards, positively and statistically significantly affect job satisfaction in the Indian banking sector. Thomaidou Pavlidou and Efstathiades’ [12] study similarly showed that IM strategies positively affect organizational culture by promoting a culture of learning and collaboration, which reflects on employees’ QWL.

In the Saudi context, Al-Khudairi’s [10] study on King Saud University employees found a strong positive relationship between IM practices and organizational citizenship behavior, noting that IM needs to be coupled with a supportive work environment to ensure job satisfaction. Rahpeyma and Pirzad’s [26] study further confirmed that IM contributes to improving employees’ quality of professional life by enhancing their commitment and providing a supportive work environment that promotes employee well-being.

2.7. *The Mediating Role of IM in the Relationship Between AI Applications and QWL*

Despite the existence of studies addressing the direct relationships between AI applications and QWL and between IM and QWL, studies exploring the mediating role of IM in the relationship between these two variables remain extremely limited, representing one of the most prominent justifications for conducting the current study.

The mediating role of IM is grounded in the integrated theoretical architecture established earlier. Building on the Socio-Technical Systems Theory (STST), AI applications (the technical subsystem) require deliberate reconfiguration of IM practices (the social subsystem) to effectively influence employee outcomes. Concurrently, from a Social Exchange Theory (SET) perspective, when organizations deploy AI in ways that enhance training, empowerment, and communication, employees perceive these as signals of organizational support, reciprocating through higher QWL evaluations [11,14]. Finally, aligning with the Industry 5.0 paradigm, human-centric technology deployment ensures that AI augments rather than threatens employees. Together, this theoretical logic predicts full rather than partial mediation, as the direct pathway from AI to QWL requires the intervening social-organizational mechanism of IM to operate effectively. Eliminating the mediator leaves no theoretically coherent direct path—a prediction consistent with the empirical results reported below. Panwar et al. [25] study provided empirical evidence supporting this mediation, finding that employee satisfaction partially mediates the relationship between AI-driven marketing forecasting and organizational financial growth, suggesting that IM can play a similar mediating role between AI applications and QWL.

Qiu et al. [9] further emphasized the necessity of studying how AI applications can integrate with IM strategies to enhance desired organizational outcomes, which the current study seeks to achieve.

2.8. *Research Gap and Study Hypotheses*

Comprehensive review of the literature reveals several critical research gaps that justify the current study:

First: Despite increasing interest in studying the impact of AI applications on the work environment, most studies have focused on specific sectors such as health and education, while studies on the government service sector in the Saudi context remain limited [17,18]. Second: While some studies have addressed the direct relationship between AI applications

and QWL, the mechanisms and mediating processes through which this relationship can be enhanced have not received sufficient attention from researchers [2,26].

Third: Despite the existence of studies on IM and its impact on organizational outcomes, studying its role as a mediating variable in the relationship between AI applications and QWL is almost non-existent in Arab literature generally and Saudi literature specifically [9,10]. Fourth: Qiu et al. [9] pointed to the scarcity of studies that integrate “big data” and “artificial intelligence” as part of IM capabilities, indicating a knowledge gap about how to use these technologies to enhance the effectiveness of IM practices in modern organizations.

Drawing on the Socio-Technical Systems Theory (STST), AI technologies require adaptive organizational practices to function effectively. The deployment of AI applications stimulates necessary investments in the social subsystem—such as training, empowerment, and internal communication—to align human capabilities with technical advancements [9,22,25]. Thus, we argue that technology deployment acts as a catalyst for internal marketing enhancements. Therefore, we posit:

H1. *Employees’ perceived use of AI applications is positively associated with IM practices.*

From a Social Exchange Theory (SET) perspective, when employees perceive robust IM practices (e.g., skill development and fair rewards), they interpret these as strong signals of organizational commitment and support. In reciprocation, employees experience enhanced job security, equity, and overall well-being [10–12]. Hence, the theoretical argument leads to the following hypothesis:

H2. *IM practices are positively associated with employees’ QWL.*

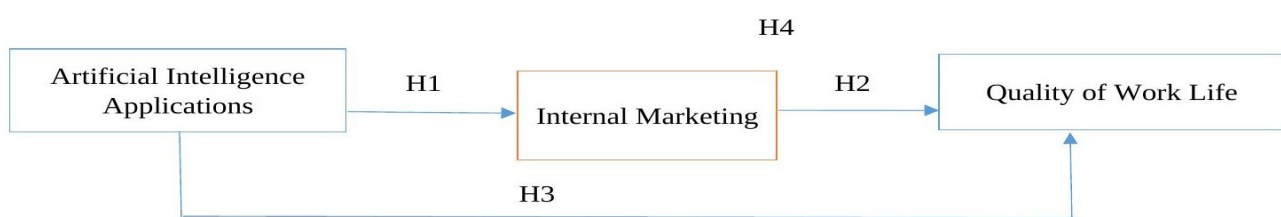
While the Industry 5.0 paradigm advocates for human-centric technology that directly augments well-being, empirical evidence suggests that perceived AI applications can reduce administrative burdens and streamline tasks, hypothetically exerting a direct positive association with work–life balance and QWL [17,18,26]. Accordingly, we hypothesize the following:

H3. *Employees’ perceived use of AI applications is positively associated with QWL.*

Drawing on our integrated theoretical framework, technological investments in AI require the organizational social subsystem (IM) to effectively translate into employee well-being [8,25]. Therefore, we hypothesize:

H4. *IM mediates the relationship between employees’ perceived use of AI applications and QWL.*

Based on the theoretical framework and literature review, Figure 1 presents the proposed conceptual research model



Source: Prepared by the author

Figure 1. The proposed conceptual model.

3. Methodology

3.1. Research Design and Approach

This study adopts a quantitative, descriptive-analytical research design employing a cross-sectional survey approach. Primary data were collected from employees across service ministries in the Kingdom of Saudi Arabia using a structured self-administered questionnaire. The study variables—AI applications, internal marketing, and QWL—were operationalised through validated multi-item scales adapted from established literature. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed via SmartPLS 4.0 to test the proposed hypotheses. PLS-SEM was specifically selected because the study's primary analytical objective is the prediction and explanation of variance in the endogenous constructs (IM and QWL), which perfectly aligns with PLS-SEM's prediction-oriented estimation logic [27]. Furthermore, it robustly handles the non-normal distributional characteristics present in our data without requiring strict distributional assumptions.

3.2. Study Population and Sample

The study population comprised employees working across service ministries in the Kingdom of Saudi Arabia, with a particular focus on ministries characterized by large workforce sizes, active AI adoption programs, and explicit alignment with Saudi Vision 2030 digitalisation objectives. The targeted ministries included the Ministry of Human Resources and Social Development, the Ministry of Health, and the Ministry of Education, selected on the basis of their documented digital transformation initiatives and relatively large and accessible employee populations.

Given the large and geographically dispersed nature of this population, a purposive-convenience sampling approach was employed, whereby the researcher distributed electronic questionnaires through institutional contact points—including departmental coordinators and human resource officers—within each participating ministry. It should be transparently acknowledged that, while efforts were made to maximize respondent diversity across organizational levels, genders, age groups, and years of experience, the absence of a comprehensive, ministry-level employee registry from which random selection could be drawn means that the procedure does not constitute simple random sampling in the technical sense. Accordingly, the sample is best characterized as a purposive convenience sample, and findings should be interpreted with this limitation in mind with respect to population-level representativeness.

The target sample size was determined using Cochran's formula, assuming a 95% confidence level and a $\pm 5\%$ margin of error, yielding a minimum target of 384 respondents. To account for anticipated non-response and incomplete submissions, 470 electronic questionnaires were distributed. Following rigorous screening for completeness and data quality, 418 valid responses were retained for analysis, yielding a usable response rate of 88.9%—a figure consistent across all sections of this manuscript. The demographic composition of the achieved sample (Table 1) reflects broad coverage across gender, age, education, and experience categories, lending descriptive breadth to the sample even in the absence of strict probability-based selection.

Table 1. Demographic characteristics of participants ($n = 418$).

Variables	Category	Frequency	Percentage (%)
Gender			
Male (1)	196	46.9	46.9
Female (2)	222	53.1	53.1
Age			

Table 1. *Cont.*

Variables	Category	Frequency	Percentage (%)
Less 25 years	47	11.2	11.2
25–35 years	41	9.8	9.8
36–45 years	133	31.8	31.8
46–55 years	118	28.2	28.2
Over 55 years	79	18.9	18.9
Educational qualification			
Diploma or below	38	9.1	9.1
Bachelor's	249	59.6	59.6
Postgraduate	131	31.3	31.3
Years of experience in ministries			
Less than 5 years	71	17.0	17.0
5–10 years	41	9.8	9.8
11–15 years	147	35.2	35.2
15–20 years	77	18.4	18.4
More than 20 years	82	19.6	19.6

3.3. Study Instrument and Measurement Procedures

The study employed a structured self-administered electronic questionnaire as the primary data collection instrument, designed in two sections: the first captured demographic and occupational characteristics, including gender, age group, educational qualification, and years of experience in service ministries; the second measured the study variables using a five-point Likert scale ranging from “strongly disagree” to “strongly agree,” selected for its widespread use and established reliability in organizational and management research. The questionnaire construction was grounded in validated scientific scales adapted to suit the context of Saudi service ministries.

Regarding the study variables, “AI Applications” (the independent variable) was operationalized as employees’ perceived extent of AI adoption and use within their ministry, measured through 11 items drawing upon the frameworks of Kosasi et al. [2] and Nurski and Hoffmann [7]. Consistent with these frameworks, the items were designed to capture the presence and functional deployment of AI tools rather than evaluative judgements about their consequences, thereby preserving the conceptual independence of the construct from both internal marketing and QWL. Items were anchored to observable AI-enabled behaviors and availability rather than to perceived outcomes. Example items include: “Virtual assistants are available in my ministry and support administrative task completion” (reflecting AI deployment for administrative functions); and “Intelligent learning platforms are used in my ministry to support professional development activities” (reflecting AI deployment for learning functions). It is acknowledged that, given the cross-sectional self-report design, some degree of evaluative coloring in respondents’ perceptions cannot be fully eliminated; however, the construct-level discriminant validity results—notably the lowest HTMT ratio in the model (QWL ↔ AI Applications = 0.300) and the Fornell–Larcker criterion confirmations—provide empirical evidence that the AI Applications construct retains sufficient independence from both IM and QWL to support the proposed structural interpretations.

“Internal Marketing” (the mediating variable) was measured through 9 items developed based on the IM scales of Muramalla [11] and Al-Khudairi [10], covering dimensions of internal communication, training and development, job empowerment, and reward systems. An example item is: “The ministry provides continuous training programmes that enhance my ability to effectively utilise AI applications.”

Finally, “QWL” (the dependent variable) was measured through 10 items formulated according to Manea [13] and Al-Balawi and Dahinen [14], reflecting dimensions of job security, work–life balance, professional development opportunities, and organizational justice. Example items include “*I feel secure in my current position within the ministry*” (job security dimension) and “*I have sufficient opportunities for professional growth and skill development in my work*” (professional development dimension). It is important to note that QWL items were deliberately anchored to employees’ subjective experience of their work conditions and well-being, without making direct reference to AI applications or internal marketing practices, in order to avoid criterion contamination and preserve the construct’s theoretical integrity as a distal outcome variable. The questionnaire items used to measure the study constructs are presented in Appendix A.

3.4. Data Collection Procedures

Field data collection adhered to strict ethical protocols, ensuring confidentiality and informed consent. Using an electronic questionnaire distributed via institutional channels within the targeted ministries, and supported by automated reminder mechanisms to maximize response completion, the study distributed 470 electronic questionnaires in total—consistent with the figure reported in the study population and sample section above. Questionnaires were screened rigorously for completeness and internal data quality prior to analysis, with responses excluded on the basis of incomplete item coverage or systematic response patterns indicating disengagement. Following this screening process, 418 valid responses were retained for analysis, yielding a usable response rate of 88.9%. The consistency of these figures across reporting sections reflects accurate data administration throughout the fieldwork process. Table 1 presents the demographic characteristics.

The sample was slightly female-dominated (53.1%), with the majority of participants aged between categories 3 and 4 (60%), holding bachelor’s degrees (59.6%), and possessing mid-to-senior experience levels (categories 3–5 combined: 73.2%), reflecting a professionally mature and educationally qualified workforce across the targeted Saudi service ministries.

3.5. Instrument Validity Verification Procedures

To ensure instrument validity, five experts reviewed the questionnaire, resulting in a high Content Validity Ratio of 0.88 [28,29]. Linguistic accuracy was secured via back-translation [30]. Despite using robust scales [31], a pilot study with 40 employees confirmed the instrument’s clarity and readiness for final application [32].

3.6. Data Analysis Method

Data analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS. Although the structural model’s three-construct configuration is technically estimable using CB-SEM or Hayes’ PROCESS macro, PLS-SEM was selected on four methodological grounds: (1) the study’s primary inferential goal is variance explanation and prediction rather than global model fit assessment, which is the domain in which PLS-SEM has comparative advantage [27]; (2) the distributional diagnostics—confirmed by Harman’s single-factor test and VIF values ranging from 1.459 to 2.986—indicated data characteristics favoring distribution-free estimation; (3) the multi-scale composite structure of the measurement instruments, each drawing on established scales adapted from multiple sources, suits PLS-SEM’s flexibility with indicator specification; and (4) PLS-SEM’s bootstrapping procedure (5000 subsamples) provides bias-corrected confidence intervals for indirect effects, offering inferential precision for mediation testing that exceeds traditional parametric alternatives such as the Sobel test [33]. All path coefficients reported throughout this manuscript are standardized estimates from the final

validated structural model, presented in full in the structural model results table below, which serves as the definitive source for all reported structural parameters.

4. Results

4.1. Common Method Bias

To mitigate common method bias risks associated with self-reporting, the study adopted a dual approach integrating procedural and statistical controls [34]. Procedurally, data confidentiality was ensured, and respondents were informed that there were no right or wrong answers, thereby reducing social desirability bias and respondent apprehension [35]. Statistically, Harman's single-factor test indicated that the first factor explained 34.2% of the total variance, below the commonly cited 50% threshold [36]. It is important to note, however, that Harman's test is widely recognized as a weak and conservative indicator of common method variance (CMV) that detects only the most severe cases of inflation; it cannot rule out more subtle forms of method-induced covariation, particularly in single-source cross-sectional surveys where conceptually adjacent constructs are measured using the same Likert-format instrument [34,37]. This caveat is especially pertinent to the IM–QWL pair, given their high inter-construct correlation ($r = 0.700$) and HTMT ratio (0.820), which, while within conventional thresholds, approaches the area at which method-induced covariation and genuine construct association become difficult to disentangle empirically. Although a full collinearity assessment confirmed VIF values (1.459 to 2.986) below the 3.3 threshold [38], providing supplementary evidence against severe CMV, we acknowledge that these post hoc techniques are insufficient on their own. The absence of a theoretically unrelated marker variable or a CFA marker technique in our survey design represents a specific methodological limitation. Therefore, the possibility that shared evaluative variance inflated the structural paths cannot be fully ruled out and must be treated as a substantive constraint.

4.2. Measurement Model Evaluation

Table 2 presents the measurement model evaluation. Convergent validity was assessed using item loadings and Average Variance Extracted (AVE). All item loadings ranged from 0.700 to 0.799, exceeding the 0.70 threshold. AVE values surpassed the 0.50 benchmark across all constructs: QWL (0.600), AI Applications (0.560), and IM (0.548). Internal consistency was established with Cronbach's Alpha coefficients ranging from 0.885 to 0.970 and Composite Reliability (CR) scores ranging from 0.916 to 0.974. While the Cronbach's alpha for AI applications (0.970) is particularly high—which can sometimes indicate item redundancy—this reflects the highly specific, interrelated functional nature of the AI tools assessed in this context. Importantly, all item-level Variance Inflation Factors (VIFs) remained below the conservative threshold of 3.0 (ranging from 2.072 to 2.986, see Table 2), confirming that while the items are strongly correlated, they do not suffer from problematic multicollinearity.

Table 2. Convergent validity, reliability, and item loadings ($n = 418$).

Latent Variable	Items	Loadings	VIF	Cronbach's Alpha	AVE	CR
(AI Applications)	AI 1	0.765	2.698	0.970	0.560	0.974
	AI 2	0.790	2.782			
	AI 3	0.738	2.414			
	AI 4	0.756	2.499			
	AI 5	0.795	2.249			
	AI 6	0.777	2.072			
	AI 7	0.752	2.940			
	AI 8	0.738	2.646			

Table 2. *Cont.*

Latent Variable	Items	Loadings	VIF	Cronbach's Alpha	AVE	CR
(Internal Marketing)	AI 9	0.782	2.906	0.885	0.548	0.916
	AI 10	0.769	2.409			
	AI 11	0.763	2.986			
	IM1	0.783	1.509			
	IM2	0.732	1.661			
	IM3	0.700	1.558			
	IM4	0.710	2.041			
	IM5	0.718	1.889			
	IM6	0.711	1.905			
	IM7	0.795	1.807			
(Quality of Work Life)	IM8	0.768	1.714	0.925	0.600	0.938
	IM9	0.738	1.459			
	QWL1	0.799	1.830			
	QWL2	0.771	1.535			
	QWL3	0.769	1.495			
	QWL4	0.746	1.895			
	QWL5	0.766	2.062			
	QWL6	0.772	2.195			
	QWL7	0.777	2.254			
	QWL8	0.779	2.229			
	QWL9	0.778	2.209			
	QWL10	0.789	2.312			

Overall, these indices confirm strong psychometric properties, demonstrating the high accuracy and reliability of the measurement scales used for the targeted sample.

4.3. Discriminant Validity: HTMT Criterion

To further corroborate discriminant validity beyond the Fornell–Larcker criterion, the Heterotrait–Monotrait (HTMT) ratio was employed as a more stringent and sensitive test [39]. The HTMT criterion requires that ratio values remain below the 0.85 threshold to confirm that constructs are empirically distinct [39]; some scholars recommend the more stringent 0.90 threshold for conceptually proximate constructs [40]. As presented in Table 3, HTMT values for IM ↔ AI Applications (0.550) and QWL ↔ AI Applications (0.300) are well within acceptable limits, indicating clear empirical separation from the independent variable. However, the HTMT ratio for QWL ↔ IM (0.820) warrants more careful interpretation. While this value satisfies the conventional 0.85 threshold, it is proximate to the boundary and substantially higher than the ratios involving AI applications, indicating that IM and QWL share a meaningful degree of systematic variance. This proximity highlights a potential conceptual overlap, given that specific IM practices (e.g., training, empowerment, and rewards) conceptually align closely with corresponding QWL dimensions (e.g., professional growth, autonomy, and equity). In the context of a single-source cross-sectional survey, this conceptual overlap and the resulting shared variance represent a substantive boundary condition, which is further addressed in the study's limitations. Because constructs are conceptually adjacent and measured using identical Likert-format scales administered simultaneously, this proximity raises the possibility that a portion of the observed IM–QWL covariation reflects shared evaluative method variance rather than a distinct substantive mediating relationship. These constructs are therefore treated as adequately—but not unambiguously—discriminant, and this measurement boundary condition is acknowledged as a substantive constraint on the interpretation of the IM → QWL path coefficient reported in the structural model.

Table 3. Heterotrait-Monotrait (HTMT) ratios ($n = 418$).

Construct Pair	HTMT Value	HTMT _{0.85}	Interpretation
IM ↔ AI Applications	0.550	Pass	Discriminant validity established
QWL ↔ AI Applications	0.300	Pass	Discriminant validity established
QWL ↔ IM	0.820	Pass	Discriminant validity established

4.4. Discriminant Validity

To verify discriminant validity, the Fornell–Larcker criterion was applied, which requires that the square root of the *AVE* for each construct exceed its correlations with all other constructs in the model [41]. As presented in Table 4, the square root of *AVE* values for AI Applications (0.748), IM (0.740), and QWL (0.775) all exceeded their respective inter-construct correlations. Notably, the highest inter-construct correlation was observed between IM and QWL (0.700), yet it remained below the corresponding *AVE* square roots of both constructs. These results confirm that each construct captures unique variance not shared with other constructs, thereby establishing satisfactory discriminant validity across all three study variables. Table 4 presents the results of this analysis.

Table 4. Discriminant validity using Fornell–Larcker criterion.

Variables	AI Applications	Internal Marketing	Quality of Work Life
AI Applications	0.748		
Internal Marketing	0.450	0.740	
Quality of Work Life	0.250	0.700	0.775

4.5. Structural Model Quality Assessment (R^2 , Q^2 , f^2)

Following confirmation of measurement model validity, the structural model was evaluated using three complementary indices. The coefficient of determination (R^2) assessed variance explained in each endogenous construct, Stone–Geisser’s Q^2 statistic confirmed predictive relevance with all values exceeding zero, and Cohen’s f^2 quantified each predictor’s relative effect size [27,42]. As presented in Table 5, AI Applications explained 20.3% of variance in IM ($R^2 = 0.203$), while combined predictors accounted for 52.4% of variance in QWL ($R^2 = 0.524$). Effect sizes ranged from small ($f^2 = 0.071$) to large ($f^2 = 1.095$), confirming the model’s adequate explanatory and predictive power. Table 5 presents the results of this analysis

Table 5. Model quality summary (R^2 , Q^2 , f^2) ($n = 418$).

Endogenous Construct	R^2	Q^2	f^2	Interpretation
Internal Marketing	0.203	0.216	AI Applications → IM: 0.255 (Medium)	Moderate explanatory power; predictive relevance established
Quality of Work Life	0.524	0.331	IM → QWL: 1.095 (Large) AI Applications → QWL: 0.071 (Small)	Moderate-to-strong explanatory power; predictive relevance established

4.6. Structural Model Evaluation and Hypothesis Testing

All path coefficients reported below are standardized estimates (β) derived from the PLS-SEM bootstrapping procedure with 5000 subsamples, as presented in Table 6. These values constitute the definitive reported parameters for the structural model; any figures cited in the abstract or earlier sections reflect the same final model and should be read as identical to those in Table 6.

The bootstrapping procedure (5000 subsamples) was applied to test the four proposed hypotheses, with results presented in Table 6. AI applications significantly predicted IM ($H1: \beta = 0.450$, $t = 9.000$, $p < 0.001$), and IM strongly predicted QWL ($H2: \beta = 0.700$, $t = 23.333$,

$p < 0.001$), supporting both hypotheses. However, the direct path from AI applications to QWL was non-significant ($H3$: $\beta = 0.050$, $t = 1.316$, $p = 0.188$), failing to support $H3$. Notably, the indirect path through IM was significant ($H4$: $\beta = 0.315$, $t = 7.159$, $p < 0.001$), confirming full mediation and supporting $H4$.

Table 6. Structural model results.

Hypothesis	Relationship	β	SD	t	p	Significance	Decision
H1	AI Applications $\rightarrow$ IM	0.450	0.050	9.000	<0.001	***	Supported
H2	IM $\rightarrow$ QWL	0.700	0.030	23.333	<0.001	***	Supported
H3	AI Applications $\rightarrow$ QWL	0.050	0.038	1.316	0.188	ns	Not Supported
H4	AI Applications $\rightarrow$ IM $\rightarrow$ QWL	0.315	0.044	7.159	<0.001	***	Supported (Full Mediation)

Note: *** indicates statistical significance at $p < 0.001$; ns indicates a non-significant relationship ($p \geq 0.05$).

This study investigated the mediating role of IM in the relationship between AI Applications and QWL among employees in Saudi service ministries. To summarize the key findings: the results revealed that AI applications significantly enhance IM practices (H1), which in turn strongly predict QWL (H2). Interestingly, the direct effect of AI on QWL was non-significant (H3), suggesting a structural pattern consistent with full mediation (H4), though the cross-sectional nature of the data warrants a cautious causal interpretation. The findings also support the growing view that the sustainability of digital transformation initiatives depends not only on technological efficiency, but also on their ability to support employee well-being and organizational quality of life.

H1. *AI Applications $\rightarrow$ IM.*

The first hypothesis was supported, confirming that AI applications positively and significantly predict IM practices. This finding suggests that as service ministries advance their AI adoption—through virtual assistants, intelligent learning platforms, and data analytics—they simultaneously stimulate improvements in internal communication, training, and employee empowerment practices. This aligns with Qiu et al. [9], who argued that AI-driven big data analytics enables organizations to better understand employee needs and customize IM strategies accordingly. It also resonates with the Socio-Technical Systems Theory [1], which advocates that technology implementation should be accompanied by organizational adaptations that serve employee well-being.

However, it is important to contextualize the magnitude of this effect. The structural model indicates that AI applications explain 20.3% of the variance in IM ($R^2 = 0.203$). While this confirms a meaningful technological influence, it also explicitly indicates that internal marketing is predominantly shaped by other organizational, leadership, and cultural factors not included in the current model. Conversely, the model explains a robust 52.4% of the variance in QWL ($R^2 = 0.524$), underscoring that when AI adoption is successfully coupled with IM practices, they collectively serve as highly effective predictors of employee well-being.

H2. *IM $\rightarrow$ QWL.*

The second hypothesis yielded the study's strongest path coefficient ($\beta = 0.700$, $f^2 = 1.095$), confirming that IM is the dominant predictor of QWL in the proposed model. This result is consistent with Al-Khudairi [10], who demonstrated a strong positive relationship between IM practices and employee outcomes in the Saudi context, and with Muramalla [11], who identified internal communication and employee rewards as the most influential IM factors on job satisfaction. The large effect size further underscores the centrality of IM in shaping employees' perceived QWL across Saudi service ministries.

As established in the theoretical framework, this strong relationship stems from the dimensional alignment between IM practices and QWL components. However, a self-critical interpretation of this exceptionally high magnitude ($\beta = 0.700$) is necessary. While it reflects the genuine strength of IM as a primary organizational conduit, it is highly probable that this effect is artificially inflated by the conceptual overlap between the constructs—such as IM ‘rewards’ mirroring QWL ‘equity.’ Furthermore, shared methodological bias stemming from single-source self-reported data likely contributes to this inflated effect, capturing a generalized positive evaluation of the work environment rather than a purely distinct causal mechanism.

H3. *AI Applications* → *QWL*.

Contrary to the expectation embedded in H3, the direct path from AI applications to QWL was non-significant ($\beta = 0.050$, $t = 1.316$, $p = 0.188$). This result warrants careful interpretation and should not be dismissed as a null or negative finding; rather, it is theoretically informative and consistent with the integrated framework advanced in this study. A methodological clarification is warranted here, however, in light of potential concerns regarding construct operationalisation. As noted in the measurement section, the AI Applications items were designed to reflect the extent of AI deployment and functional availability within the ministry, drawing on Kosasi et al. [2] and Nurski and Hoffmann [7]. Although some items reference functions that could carry evaluative connotations (e.g., platforms supporting professional development), the construct’s discriminant validity from QWL—as evidenced by the lowest HTMT ratio in the model (0.300) and satisfactory Fornell–Larcker separation—provides empirical grounds for treating the two constructs as sufficiently distinct. Accordingly, the non-significant direct path does not appear to be an artifact of construct overlap; rather, it reflects a genuine structural finding consistent with full mediation. From a Socio-Technical Systems Theory perspective, the non-significance of the direct path confirms that AI, as a technical subsystem element, lacks an autonomous pathway to human outcomes and requires the mediation of the social subsystem through IM practices. From a Social Exchange Theory perspective, AI applications do not constitute direct organizational resources that employees can exchange for well-being; they must first be converted into perceived organizational support through IM. This non-significant direct effect warrants a deeper comparative analysis with prior studies that reported positive direct impacts of AI on QWL [17,18]. A critical review suggests several contextual and methodological reasons for this divergence. First, the bureaucratic nature of the public sector differs fundamentally from agile private sectors; institutional rigidity may buffer direct technological impacts, requiring formal IM initiatives to translate them into employee benefits. Second, the level of AI maturity in these ministries may still be in transitional phases, where technology acts as a backend administrative tool rather than an autonomous well-being enhancer. Third, the local organizational culture places a premium on human interaction and managerial support, making QWL highly dependent on how leaders manage the transition (IM) rather than the technology itself. By isolating AI from IM, our findings confirm that technology alone does not directly improve QWL, strongly aligning with Nurski and Hoffmann [7]. Methodologically, the confidence interval for this path includes zero, confirming the non-significance and supporting the interpretation of full rather than partial mediation [43].

H4. *AI Applications* → *IM* → *QWL*.

The most theoretically significant finding is the pattern consistent with full mediation ($\beta = 0.315$, $t = 7.159$, $p < 0.001$), whereby the indirect path through IM accounts for the

entirety of the observed covariation between AI applications and QWL, with the direct path remaining non-significant. This pattern is consistent with the theoretical prediction that IM functions as the complete organizational mechanism linking AI deployment to employee well-being; however, given the cross-sectional design of the study, this finding should be interpreted as evidence of structural correspondence between the data and the proposed model rather than as causal confirmation of the mediation sequence. The data support the theoretical model but cannot, by design, establish the temporal ordering necessary to rule out alternative causal configurations—including the possibility that organizations with stronger IM systems are more likely to adopt AI effectively or that employees with higher baseline QWL evaluate both IM and AI more favorably.

Third, from a theoretical standpoint, this pattern is consistent with the STST prediction that joint technical-social optimization is the necessary condition for human outcomes; the SET prediction that organizational resources (IM) mediate the AI–well-being exchange; and the Industry 5.0 normative claim that human-centric practices should constitute the deliberate priority of technological transformation. It bears emphasis that cross-sectional covariation, however structurally coherent, cannot adjudicate among competing causal accounts; the theoretical frameworks invoked here provide the logical rationale for the hypothesized causal sequence, but their empirical confirmation requires longitudinal or experimental designs capable of establishing temporal ordering. This finding is consistent with the Industry 5.0 philosophy [1], which positions human-centric organizational strategies as indispensable mediators between technological advancement and employee well-being and extends Awad et al. [24] work on the mediating role of organizational variables into the Saudi government context.

5. Contribution

This study makes several meaningful theoretical and practical contributions that advance understanding of the complex interplay between AI applications, internal marketing, and QWL within the Saudi government sector.

5.1. Theoretical Contributions

This study offers a novel theoretical contribution by constructing and empirically validating an integrative model that positions IM as a full mediator between AI applications and QWL. While prior research has examined the direct relationship between AI and employee well-being [3,17,18] or the independent role of IM in shaping job satisfaction [10,11], no previous study in the Arab and Saudi context has integrated these three variables within a single explanatory framework.

A methodological caveat must be acknowledged alongside these contributions. The operationalisation of AI applications as a perceived-use construct—rather than an objective administrative measure of AI adoption—introduces the inherent limitation of self-report data in cross-sectional designs, whereby respondents' evaluative schemas may subtly influence their ratings across constructs. While the discriminant validity evidence presented in this study (HTMT = 0.300 for QWL ↔ AI applications; Fornell–Larcker criterion satisfied) offers empirical reassurance against severe construct overlap, future research should consider supplementing perceptual AI measures with objective indicators of AI deployment intensity (e.g., system usage logs, AI budget allocations, or IT infrastructure indices) to more cleanly separate AI adoption as an antecedent from its perceived consequences.

Beyond the empirical confirmation of full mediation, the study advances theoretical knowledge in three additional respects. First, it operationalises the theoretical integration of STST, SET, and Industry 5.0 in a single testable model, demonstrating that these frameworks

are not merely additive but structurally complementary: STST specifies the macro-level design logic (joint optimization of technical and social subsystems), SET specifies the micro-level motivational mechanism (reciprocity in exchange of organizational resources), and Industry 5.0 specifies the normative direction (human primacy in technological transformation).

Prior studies in this domain have typically drawn on a single theoretical lens (e.g., STST alone or SET alone), limiting their explanatory purchase. The present study's multi-theoretical architecture is more powerful precisely because each framework explains a distinct aspect of the mediational process. Second, the finding of indirect-only mediation [44]—whereby the direct AI → QWL path is entirely absent—resolves a persistent ambiguity in the literature: prior studies reporting direct AI–well-being relationships may have been observing model misspecification artifacts rather than genuine direct effects, as IM-type variables were systematically omitted from those models. Third, the study establishes the theoretical transferability of STST to an Islamic public-sector context in the Arab world, where the social subsystem is shaped by culturally specific values around collectivism, *wasta*, and formal organizational hierarchy—factors that may amplify the role of IM as an interpersonal trust-building mechanism.

The confirmation of full mediation represents a theoretically significant finding, as the non-significant direct path from AI applications to QWL suggests that technology alone is insufficient to enhance employee well-being; rather, its impact is entirely channeled through IM practices. This finding extends Socio-Technical Systems Theory [1] by empirically demonstrating that the social system serves as the indispensable bridge between technical advancement and human outcomes. Furthermore, by establishing that AI's benefit to employees is mediated by people-oriented organizational practices, the study provides quantitative evidence supporting the Industry 5.0 paradigm [1] within a government service context.

A fourth theoretical contribution concerns the study's engagement with QWL as a theoretically differentiated rather than undifferentiated construct. While the structural model necessarily treats QWL as a composite reflective outcome—consistent with established measurement practice in the field [13,14]—the theoretical framework advanced in this study articulates three dimension-specific mechanisms through which AI applications are expected to influence QWL: the demand-reduction mechanism (targeting workload and work–life balance), the skill-augmentation mechanism (targeting professional development and competency growth), and the justice-signaling mechanism (targeting procedural and distributive fairness perceptions). Furthermore, the study specifies how each IM dimension maps onto corresponding QWL components—training and development onto professional growth; internal communication onto participation and inclusion; empowerment onto autonomy and control; reward systems onto justice perceptions—thereby providing a theoretically coherent account of why IM constitutes a dimensionally sufficient mediating mechanism rather than merely a correlated organizational practice.

This multi-mechanism theoretical architecture represents an advance over prior studies that either treat QWL as a generic well-being composite without specifying which components are in play [17,18] or examine IM's effects on single QWL proxies such as job satisfaction without considering the broader dimensional structure of well-being [10,11]. Future research should empirically test these dimension-specific pathways through confirmatory second-order or profile analyses that disaggregate QWL into its constituent dimensions, thereby providing finer-grained evidence about which aspects of employee well-being are most responsive to AI-enabled IM investments. The study additionally contributes to emerging discussions on human-centered and sustainable digital transformation

within public-sector organizations by highlighting the importance of employee well-being as a central outcome of AI-enabled organizational change.

5.2. Practical Contributions

From a managerial perspective, this study delivers actionable insights for decision-makers across Saudi service ministries. The finding that the data are consistent with IM fully mediating the AI-QWL relationship suggests that the association between AI adoption and employee well-being may be contingent upon the concurrent presence of deliberate IM strategies—encompassing internal communication, training and development, job empowerment, and reward systems. While the cross-sectional design precludes causal inference, this pattern offers practitioners a theoretically grounded and empirically supported rationale for treating IM investment as a likely necessary condition for realizing well-being returns from AI deployment, pending replication in longitudinal designs.

6. Recommendations

Based on the study's findings, the following recommendations are directed at decision-makers and human resource managers in Saudi service ministries.

First, the study's findings offer a strong empirical basis for integrating IM as a core component of AI implementation strategies rather than treating it as a peripheral activity. The observed pattern—in which the association between AI applications and QWL operates entirely through IM practices—suggests that AI adoption initiatives are more likely to yield measurable improvements in employee well-being when accompanied by parallel IM programs that prepare employees, address technology-related concerns, and communicate the purpose and benefits of digital transformation clearly and transparently. Although the cross-sectional design means this relationship should be interpreted as associative rather than definitively causal, the theoretical coherence of the proposed mechanism and its consistency with findings from related literature [9,25] provide sufficient grounding for evidence-informed managerial action pending longitudinal confirmation.

Second, directly addressing the training and development dimension of internal marketing, ministries should invest substantially in AI-focused training programs that equip employees with the competencies required to engage effectively with AI tools. Structured learning pathways supported by intelligent learning platforms can build digital confidence, reduce technology-related anxiety, and enhance employees' sense of professional competence.

Third, to operationalize the internal communication dimension, strengthening bilateral communication channels is essential to fostering trust and reducing resistance to technological change. Ministries should establish dedicated communication platforms that keep employees consistently informed about AI developments and available support resources, reinforcing their sense of psychological safety.

Fourth, reflecting the job empowerment dimension, decision-makers must ensure that AI tools are implemented as augmentative support rather than mechanisms of directive algorithmic management. Empowering employees with the autonomy to leverage AI in their daily tasks fosters a sense of control and active participation in decision-making.

Fifth, explicitly linked to the Reward Systems dimension, fair and transparent reward and recognition frameworks should be developed to acknowledge employees who successfully adapt to AI tools in their work. Structured incentive mechanisms signal institutional appreciation and reinforce positive behavioral adaptation to technological change.

7. Limitations and Future Research

Several critical limitations must be robustly and transparently acknowledged. First, the cross-sectional design prevents the establishment of causal inferences. Second, the reliance on subjective data from a single source introduces potential methodological biases. Third, utilizing a purposive convenience sample inherently restricts the generalizability of the findings to the broader population. Fourth, as noted in the measurement evaluation, there is a potential for conceptual overlap between IM and QWL constructs, which may artificially inflate their association. Finally, the current study lacks testing for differences between ministries or functional organizational levels, thereby treating the public sector as a largely homogenous entity.

To address these constraints, future research should employ longitudinal prospective studies to examine the evolving impact of AI over time. Methodologically, scholars are encouraged to conduct multi-source studies that combine employee and managerial perspectives with objective performance data. Furthermore, comparative studies are highly recommended, particularly between the public and private sectors, or between ministries with varying levels of digital maturity. Lastly, future models should test the dimensions of quality of work life separately rather than treating them as an overall indicator, as specific dimensions (e.g., workload vs. autonomy) may be distinctly more affected by AI deployment than others.

8. Conclusions

This study examined the mediating role of IM in the relationship between AI applications and QWL among employees in Saudi service ministries. The findings revealed that AI applications are positively associated with IM practices, which in turn constitute the dominant predictor of QWL. The direct association between AI and QWL was non-significant, supporting a statistical pattern structurally consistent with full mediation, while acknowledging that longitudinal designs are needed to definitively confirm causality.

Theoretically, this study makes a significant contribution by integrating Socio-Technical Systems Theory, Social Exchange Theory, and Industry 5.0 into a cohesive framework, providing robust empirical evidence that technology alone does not drive well-being without intervening organizational mechanisms. Practically, the study offers critical public-sector implications: as government institutions pursue rapid digital transformation under Saudi Vision 2030, they must actively deploy comprehensive IM strategies—encompassing communication, training, empowerment, and rewards. Doing so ensures a sustainable, human-centered digital evolution that successfully enhances both operational efficiency and employee quality of work life.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Research Ethics Committee of Jouf University (protocol code HAPO-13-S-001, 11342 and 20 October 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ethical and privacy restrictions in accordance with the conditions established by the Research Ethics Committee at Jouf University.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Questionnaire Items Used in the Study

Study: The Mediating Role of Internal Marketing in the Relationship Between Artificial Intelligence Applications and Quality of Work Life

No.	Code	Item
Section I: Artificial Intelligence Applications (11 Items)		
1	AI1	Virtual assistants are available in my ministry and support administrative task completion.
2	AI2	Virtual assistants in my ministry are effective in scheduling meetings and organizing official correspondence.
3	AI3	I use virtual assistants to search for information or answers related to my work tasks.
4	AI4	Virtual assistants help me save time and effort in completing my work tasks.
5	AI5	Using virtual assistants improves my efficiency and productivity at work.
6	AI6	I wish to expand the use of virtual assistants in my work in the future.
7	AI7	Intelligent learning platforms are used in my ministry to support professional development activities.
8	AI8	Intelligent learning platforms in my ministry provide personalized educational content tailored to individual needs.
9	AI9	Intelligent learning platforms enable me to track my progress and evaluate my performance regularly.
10	AI10	Intelligent learning platforms facilitate access to diverse learning resources and support continuous learning.
11	AI11	Using intelligent learning platforms improves my opportunities for professional growth and career development.
1	IM1	Management uses AI tools to analyze employee data and accurately understand their needs and expectations.
2	IM2	Intelligent technologies in the organization help classify employees according to their skills to provide tailored occupational services for each group.
3	IM3	Intelligent systems provide me with easy channels to communicate my voice and suggestions to senior management.
4	IM4	Smart digital tools are used to promote the ministry's vision and goals to employees in an engaging and persuasive manner.
5	IM5	Smart applications eliminate organizational barriers, facilitating direct communication among different departments.
6	IM6	The organization provides me with smart, personalized training programs suited to my career path.
7	IM7	I feel that the technologies used are designed to empower me to perform my work easily, not merely to monitor me.
8	IM8	AI systems ensure fairness and transparency in evaluating my performance, enhancing my sense of appreciation.
9	IM9	Intelligent systems link my achievements to rewards and incentives in an immediate and accurate manner.
1	QWL1	I feel secure in my current position within the ministry.
2	QWL2	I perceive my job as stable and not threatened by unexpected risks.
3	QWL3	I am able to achieve an acceptable balance between work demands and my personal and family commitments.
4	QWL4	My ministry provides me with sufficient flexibility in organizing my time and work approach.
5	QWL5	I have sufficient opportunities for professional growth and skill development in my work.
6	QWL6	My ministry supports my career path through the provision of continuous training and development.
7	QWL7	Performance evaluation procedures in my ministry are objective and transparent.
8	QWL8	Work is distributed among employees in a fair manner that takes into account competencies and specializations.
9	QWL9	I enjoy positive professional relationships with my colleagues and supervisors in the work environment.
10	QWL10	A culture of mutual respect and cooperation among employees prevails in my ministry.

All items were measured using a five-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Agree, 4 = Agree, 5 = Strongly Agree).

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