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Research Article

Artificial intelligence: Its implementation in philippine healthcare institutions

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ABSTRACT

Artificial intelligence (AI) is rapidly gaining attraction in numerous private and public organizations in the Philippines. It is a technology used in many aspects of human resource functions such as in education institutions. Thus, this study investigated how human resource practitioners in healthcare institutions across two Bulacan towns perceived AI. Two hundred and one electronic survey questionnaires (distributed via Google Forms) were sent to different practitioners in hospitals and clinics. The researchers aimed to investigate how perceived risks and technological awareness affected the participants. They also sought to examine the relationship between human resource functions and AI. The researchers used PLS-SEM for the quantitative research design of the study. Findings showed a significant correlation between AI and personal innovativeness, and between human resource functions and both personal innovativeness and technological awareness. Conversely, no positive relationship was found between human resource practitioners' use of AI and their HR functions. Practitioners were not yet ready to fully implement AI and reap its benefits. Finally, perceived risks significantly affected the relationship between human resource functions and technological awareness. The results strongly suggest that more Philippine health professionals will eventually adopt this technology to streamline its use, reduce errors by practitioners, and improve organizational performance.

Keywords: Artificial Intelligence (AI); healthcare; human resource functions; personal innovativeness; technological awareness

1. Introduction

Artificial intelligence (AI) has been applied in several digital and non-digital features. it simulates tasks requiring human intellect, such as reasoning, sensory comprehension, adaptation, and deep learning [1]. it is widely used for web searches, medical services, and mental health assistance, particularly via mobile platforms, improving mental health and wellness by bridging healthcare gaps [2]. It transforms industries by

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enhancing efficiency, precision, and decision-making [3]. In HR management, AI automates repetitive tasks, improves decision-making, and boosts efficiency. AI tools analyze data to identify patterns, aiding in recruitment, employee retention, and talent management [1]. In the healthcare sector, AI is used in clinical laboratory screening, genetic diagnosis, imaging diagnostics, and health-related communications [4]. AI techniques are applied to cardiology, neurology, and cancer, utilizing both structured and unstructured medical data [1-5]. Innovations in AI such as deep learning [6] may also be addressed.

In the Philippines, artificial intelligence can play an important role in the healthcare sector. It can perform accurate analysis of large datasets in government agencies such as the Department of Health, PhilHealth, and even hospitals. It can help in the recruitment and deployment optimization of employees. In addition, it can help a lot in conducting activities such as Training and Capacity Building. Performance Monitoring and Management can also be conducted with the aid of AI.

However, top management in the healthcare systems in the Philippines may encounter several challenges in adopting AI. Bautista et al. [7] stress that even if many Filipino healthcare workers are aware of AI, they lack proper exposure and formal training. They resist to change; thus, they possess limited digital literacy. Lack of financial support, [8] aside from barriers like poor connectivity and outdated equipment [9] prevent the use of AI among Filipino healthcare employees. Tellmedico [10] found out that patients still cling to the traditional face-to-face consultations. They feel uncomfortable when introduced to automated systems, thus rejecting AI-powered tools such as symptom checkers, potentially leading to self-medication or incorrect diagnoses.

The challenges met or observed in the healthcare sector which can slow down the adoption of AI prompted the researchers to examine the readiness of Human Resource practitioners in healthcare to adopt AI in their workplace. Specifically, the study aims to investigate the relationship between AI and Human Resource Functions (HR), AI and personal innovativeness, AI and technological awareness, HR and personal innovativeness, HR and technological awareness, as well as technological awareness and perceived risks.

2. Review of related literature

2.1. Artificial intelligence and human resources

Human resources (HR) is a business department handling people-related functions, including pay, benefits, hiring, onboarding, performance management, training, and organizational development and culture. Senior staff must advise HR on how financial, planning, and performance decisions impact people. Human capital is crucial for achieving operational goals [11].

Munir et al. [12] highlight that HR is essential in production processes, as operations would not run smoothly without adequate human resources. HR management has evolved strategically due to economic, political, social, and technological developments, driving operational excellence and competitiveness [13]. Rahayuningsih et al. [14] argue that effective administration requires highly qualified personnel to optimize operations and enhance employee performance.

AI revolutionizes everyday work with minimal human intervention, enhancing organizational performance with speed and accuracy. It supports hiring by automating tasks like sending texts, evaluating resumes, and verifying references, though complex scenarios still need human oversight [15, 16]. Bhardwaj et al. [17] note that many HR professionals do not understand AI's potential to elevate HR services, including hiring, payroll, and self-service interactions. AI enhances operational comprehension through massive HR data analysis. Zuhair et al. [18] agree that AI transforms HR operations, especially in healthcare, by simplifying recruitment, boosting engagement, and improving efficiency. AI-driven training ensures that healthcare professionals in the Philippines stay updated with the latest practices [19].

2.2. Anchored model: TAM

Davis developed the Technology Acceptance Model (TAM), which has been proven effective in promoting technology adoption. TAM considers how perceived utility (PU) and perceived ease of use (PEOU) influence technology acceptance. *PU* refers to the belief that using technology enhances performance, while *PEOU* measures the perceived effortlessness of technology use [20-22.

2.3. Hypothesis development

The toughest responsibility for human resource managers is narrowing down and reviewing credentials from a wide pool of applications in order to select the most qualified applicant for the position. Artificial intelligence programs can help scan the curriculum vitaes of applicants, assess them, and reject those that are unsuitable for the position [23].

2.4. Human resource function and artificial intelligence

AI uses algorithms to develop Central AI, which provides precision and consistency to routine tasks by fusing accurate information with quick computational capabilities. The size of every organization is determined by its capacity to efficiently integrate personnel, procedures, and resources in order to produce transformative value at the lowest feasible cost [17]. Digital platforms and automated apps could assist with repetitive work, freeing up human labor to concentrate more on creativity and ideas. Artificial intelligence (AI) systems may learn and predict specific outcomes statistically before deciding based on a range of parameters [24]. Thus, *human resource functions correlate with artificial intelligence (H1).*

Personal inventiveness can affect how healthcare organizations and professionals view and use technology in relation to healthcare and artificial intelligence to enhance patient experiences and streamline healthcare procedures [25]. Artificial intelligence (AI) platforms mostly offer applications focused on individual development, such as turning textual materials into images. Artificial intelligence learning systems could be used more effectively to engage employees and encourage creative learning among them [26]. Thus, it is hypothesized that *human resource functions are influenced by personal innovativeness (H2).*

2.5. Human resource and technological awareness

Artificial intelligence is not well understood or utilized by Human Resource managers and staff [27]. Healthcare delivery has changed due to technological awareness. Therefore, in order to recruit, nurture, and keep the best staff, human resource managers need to be updated on the most recent technological developments [27]. Healthcare providers can benefit from possibilities for technological awareness in the context of education and career advancement. This technology can help human resource employees with worker productivity tracking and feedback [7].

Human Resource specialists that stay up-to-date on technology developments can attract and retain top people while adapting to the constantly evolving needs of the healthcare sector. Fortunately, the degree of technology literacy of those involved determines whether artificial intelligence is successfully implemented and used in human resource functions [28]. Thus, *human resource functions are influenced by technological awareness (H3).*

2.6. Personal innovativeness and artificial intelligence

A person's degree of inner creativity indicates how ready and able they are to take in and apply new ideas and technologies. But integrating AI into HR procedures demands an appropriate amount of human creativity from HR specialists. Technically savvy and creative HR practitioners are more likely to successfully integrate artificial intelligence into HR operations [29]. Artificial intelligence is more likely to be adopted by and successfully incorporated into the duties of skilled and inventive human resource specialists, which could ultimately enhance HR operations as well as patient outcomes. Therefore, *personal innovativeness is affected by Artificial Intelligence [H4].*

2.7. Perceived risk on technological awareness and artificial intelligence

The perception of risk may affect the ability of a company to attract highly skilled individuals. Additionally, influencing perceived risk refers to how well learning and skill-building efforts work [30]. Another aspect of personality that might improve productivity and boost openness is perceived risk [31].

Studies have affirmed that a subjective assessment of the possible advantages of implementing cutting-edge technology is known as *perceived risk*. Concerns around the safety of information, confidentiality, and the possibility of technological faults or malfunctions are all part of this method of operation [32-34].

Competence, along with comprehension and understanding of the people or organizations in connection with recent advances in technology, is referred to as technological awareness, being familiar with telemedicine and electronic health records (EHRs) [35].

AI-based systems, in contrast to other technologies (such as self-service technologies), function independently or with minimal guidance, frequently taking the place of individuals [36-37]. In order to lower obstacles for clients using artificial intelligence (AI) technologies, businesses need to know how to implement them [38]. Based on the findings of previous publications and their suggestions, it is hypothesized that *technological awareness has some implications of perceived risks (H5) and artificial intelligence influences technological awareness (H6).*

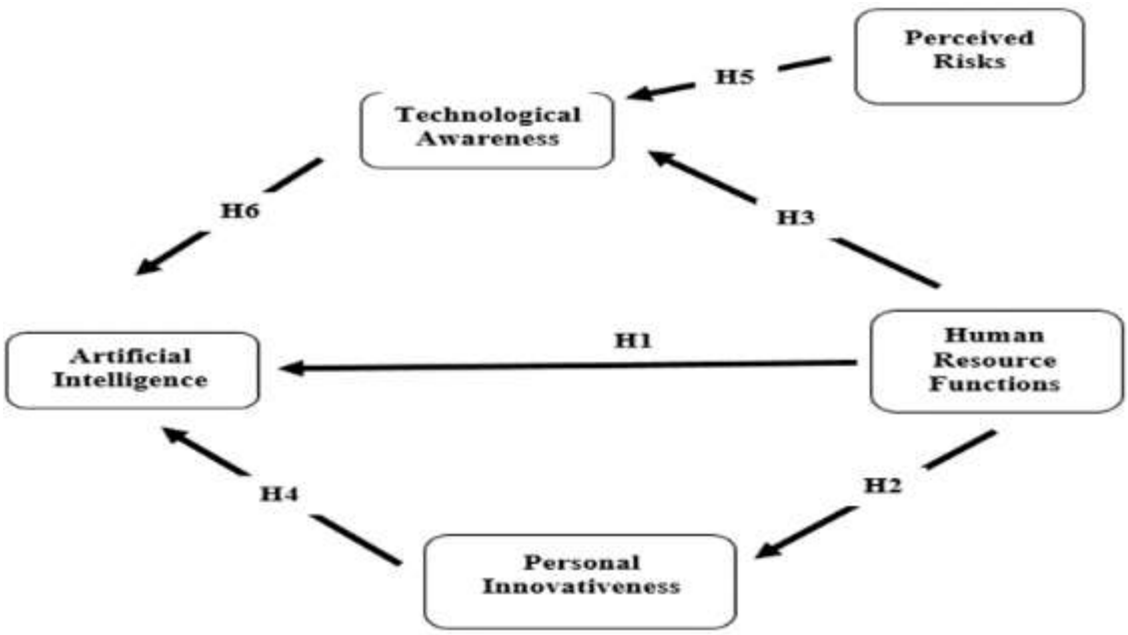

Figure 1. Hypothetical framework suggested for the study

2.8. Methodology

2.8.1. Research design

This study adopted a quantitative research design to examine causal relationships among selected variables. Data collection was conducted via Google Forms, allowing for broad reach and efficient gathering of responses. Statistical techniques were applied to analyze and validate the relationships between variables, ensuring that the research remained empirical, objective, and measurable with precision. The design incorporated computational, mathematical, and statistical tools to identify patterns and draw conclusions. Graphs and tables generated from the raw data supported visual analysis and interpretation of findings [39–41]

To further strengthen the research design in future studies, incorporating qualitative methods, such as interviews or focus groups, is recommended. These can provide richer contextual insights into human resource professionals' experiences and perceptions nuances that may not be fully captured by quantitative instruments. This mixed-methods approach would deepen the understanding of the underlying factors influencing attitudes and behaviors toward AI and technology adoption in human resources.

2.8.2. Research instruments

A structured questionnaire employing a Likert scale, known for its reliability in assessing attitudes and perceptions, was used to collect data [47]

The data were analyzed using SmartPLS version 4.1.0.1, a software tool for structural equation modeling (SEM) known for its intuitive graphical interface. As noted by Hair et al. (2021), SmartPLS effectively models latent variables and visualizes path relationships among indicators and constructs [41, 57]

For future research, enhancing transparency in instrument development is vital. This includes clearly documenting the development process of questionnaire items, detailing modifications based on pilot testing, and publicly sharing the finalized survey instrument. These practices will strengthen the instrument's credibility, replicability, and alignment with best practices in measurement validation.

2.8.3. Participants and sampling techniques

The study targeted human resource employees from healthcare institutions in Region 3 of the Philippines. A total of 201 respondents participated, recruited via online dissemination and personal outreach. A non-probability sampling method was employed, combining purposive sampling—to ensure that respondents had relevant HR experience—and convenience sampling, to maximize participation based on accessibility [54]

A pilot test was conducted with 20 HR professionals from a general hospital to ensure the clarity and relevance of questionnaire items. Feedback from this process led to refinements that improved the usability and accuracy of the instrument.

While these methods provided practical benefits for early-stage exploration, future research is encouraged to adopt stratified sampling techniques to reduce bias and enhance generalizability. This shift would allow for more robust comparisons across institutions, roles, and levels of experience and would ensure that the sample better reflects the broader HR population in healthcare settings.

2.8.4. Measurement of construct reliability and validity

To establish construct validity, both convergent and discriminant validity were evaluated. Convergent validity was considered adequate when the Average Variance Extracted (AVE) reached or exceeded 0.50, suggesting that the items effectively represented their respective constructs. Discriminant validity ensured that constructs were sufficiently distinct from each other, which is critical for confirming the measurement model's validity.

3. Results and discussion

3.1. PLS algorithm report: Construct reliability and validity

Nevertheless, Figure 2 shows that dependability is supported by a suggested composite and a value greater than 0.7 for Cronbach's alpha. Convergent validity is proportional to the 0.7 obtained for every construct: perceived risk, artificial intelligence, human resource function, personal innovativeness, and technological awareness; therefore, it is valid.

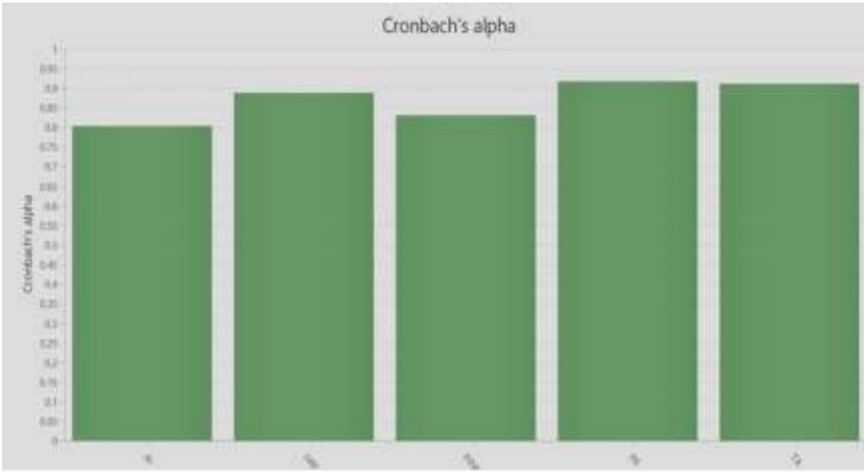

Figure 2. Cronbach's Alpha

Figure 3 illustrates the validity of the constructs based on the average extracted variance (AVE) of perceived risk, artificial intelligence, human resource function, personal innovativeness, and technological awareness, all exceeding the recommended 0.5 [55-56, 41, 59] value.

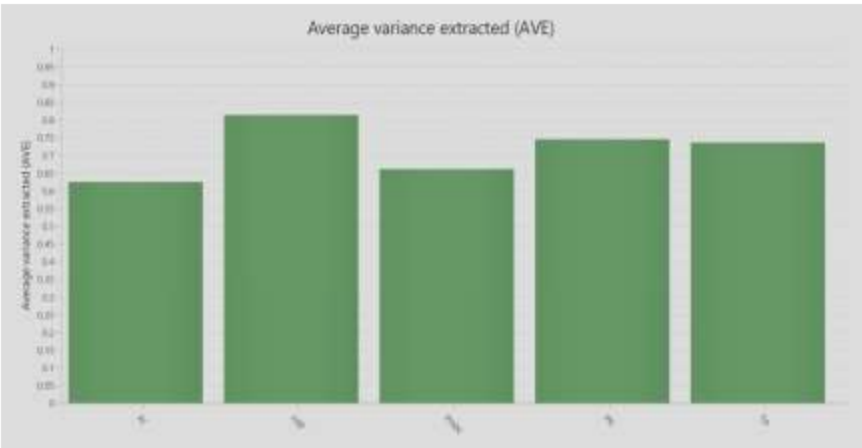

Figure 3. Average Variance Extracted

3.2. Discriminant validity

Discriminant validity can be obtained using Heterotrait-monotrait (HTMT) correlation ratio and indicator cross-loading [60]. The lowest value of 0.177 is associated with perceived risk to human resource functions. However, to determine the discriminant validity of the construct, HTMT threshold of less than 0.85 was used [39]. The achieved discriminant validity using the HTMT ratio is shown in Table 1.

Table 1. Heterotrait-Monotrait Ratio

	AI	HRF	PINN	PR	TA
AI					
HRF	0.360				
PINN	0.791	0.689			
PR	0.272	0.417	0.293		
TA	0.466	0.651	0.797	0.324	

[a] *Discriminant validity- Heterotrait-monotrait ratio (HTMT)-Matrix*

Discriminant validity-**Table 2** shows the suggested and approved tool for examining the impact of AI on HR functions in the healthcare context of the Philippines. The construct reliability and validity quality criteria, composite reliability (CR), average variance extracted (AVE) 0f 0.5, rho-A, and Cronbach's alpha composite reliability of 0.7 that were applied are summarized in Table 2.

Table 2. Construct's validity - reliability: retained items

Artificial Intelligence (AI) : Alpha (0.803); Rho (0.839); Comp (0.869); Ave (0.624)	**FA**
AI 2: Artificial Intelligence in hospitals helps improve clinical decision-making among employees.	0.849
AI 3: Artificial Intelligence in hospitals can hasten the delivery of direct care for patients.	0.842
AI 5: An ethical principle is appropriate for Artificial Intelligence to be used in the healthcare sector.	0.716
AI 6: Artificial Intelligence reduces healthcare waiting times.	0.743
*Technological Awareness (TA): Alpha (*0.910); *Rho (*0.919*);* Comp (0.933); Ave (0.735)	***FA***
TA 1: I feel great for being one of the first to purchase SI.	0.841
TA 2: High-tech purchases make me happy.	0.872
TA 3: Being one of the first to use SI makes me excited.	0.912
TA 4: I wish I could be one of the owners of cutting-edge technology items.	0.847
TA 5: I love to buy new technology items in the market.	0.812
*Personal Innovativeness (PINN): Alpha (*0.830); *Rho (*0.841*);* Comp (0.886); Ave (0.660)	***FA***
PINN 1: I have always wanted to use new technology in my work.	0.747
PINN 2: Using new technology is an acceptable solution to my current work.	0.853
PINN 4: I love searching for the latest technology in the market.	0.852
PINN 5: I would love that my current company adapt the latest technologies in the near future.	0.793
*Perceived Risk (PR): Alpha (*0.916); *Rho (*0.969*);* Comp (0.936); Ave (0.744)	***FA***
PR 1: When Artificial Intelligence is used, my personal data cannot be kept private.	0.801
PR 2: When using Artificial Intelligence, I fear that my personal information may be stolen by others.	0.875
PR 3: Learning to use Artificial Intelligence in the healthcare institutions entails too much time.	0.870
PR 4: Integrating AI in the healthcare sector makes me feel nervous because it might have errors.	0.874
PR 5: I am worried to use AI because other people may be able to access my information.	0.891
*Human Resource Functions (HRF): Alpha (*0.887); *Rho (*0.936*);* Comp (0.929); Ave (0.813)	***FA***
HRF 3: HR managers should conduct online and face-to-face seminars and workshops about the use of AI.	0.877
HRF 4: Artificial Intelligence can help monitor employees' performance in the workplace.	0.927
HRF 5: Tracking the performance of employees through AI can save time among busy HR managers.	0.900

[a] *Factor loading: Alpha = Cronbach's alpha, Rho = Composite reliability Rho c, Comp = Composite reliability RhoA,*

AVE = Average variance extracted

Figure 4 illustrates the retained factor loading and the R-squares among the elements influencing the adoption of AI.

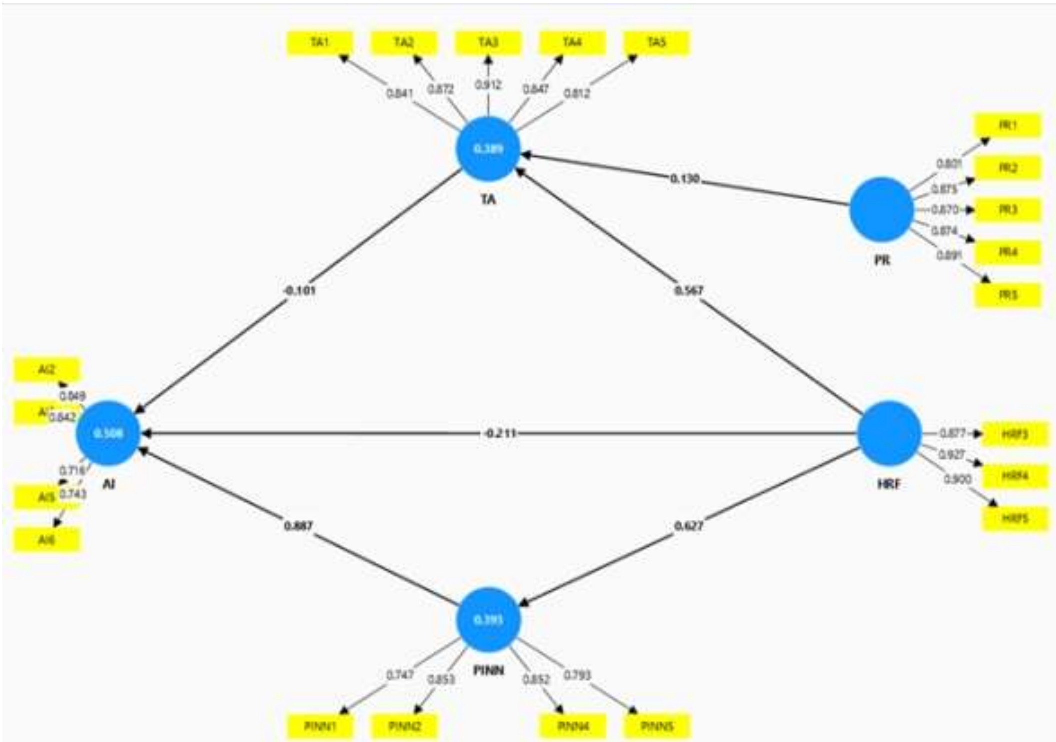

Figure 4. Algorithm model on the impact of artificial intelligence toward human resource functions

3.3. Bootstrap report: path coefficients

The *p*-values, standard deviation, and *t*-statistics make up the pathway that the coefficients construct. The threshold for statistical significance is set at 0.05 [41]. The values of the Path Coefficients are demonstrated in **Table 3**.

Table 3. Path Coefficients

Dimension	Sample Mean (M)	Standard Deviation (STDEV)	*T*-Statistics (|O/STDEV|)	*P*-Values
HRF→AI	-0.274	0.347	0.608	0.543
HRF→PINN	0.626	0.218	2.876	0.004
HRF→TA	0.580	0.176	3.221	0.001
PINN→AI	0.846	0.321	2.767	0.006
PR→TA	0.206	0.215	0.604	0.546
TA→AI	-0.081	0.382	0.265	0.791

Note: *AI = Artificial intelligence, HRF = Human resource function, PINN = Personal innovativeness, PR = Perceived risk,*

TA = Technological awareness

3.4. Discussion based on bootstrap report

Table 3 shows that human resource functions regressed on artificial intelligence (HRF→AI) with a *p*-value of 0. 543 (H1), where $p > 0.05$. This indicates that human resource functions toward artificial intelligence are not supported. This suggests that the human resource employees in the selected cities in Region 3 of the Philippines who participated in this study are familiar with artificial intelligence but somehow are not yet ready to adapt artificial technology in all of their work functions. The outcome of this study is contrary to Jia et al.'s [61] finding that AI can benefit businesses competitively by consistently improving the performance of HR personnel. Thus, the researchers conclude that the result found is not supported but should be explored in studies to be conducted in the future. In reference to Table 3, it can be gleaned that the human resource functions have a positively significant relationship to personal innovativeness (HRF→PINN) with a p-value of 0.004 (H2), $p<0.05$. This is indicative that human resource functions towards personal innovativeness is supported. In relation to Popa et al.'s [62] study, by becoming the catalyst for a social environment that nurtures creativity, commitment can help employees perform in a manner that advances the goals of the business. This shows that the human resource functions are made easy because of employee's personal innovativeness. Therefore, the connection is found to be positively related in human resource functions.

As shown in **Table 3**, the human resource functions are positively significant in relation to technological awareness (HRF→TA) with a p-value of 0.001 ($p<0.05$). The third hypothesis (H3), "Human resource functions have been influenced by technological awareness" is thus supported. This is further related to Malik et al. [63]. While the roots of technology in HRM stretches back to the industrial age, innovations in technology have only changed the availability of both mental and physical solutions. However, technological advances are gradually delivering replacements for human tasks requiring human communication. This indicates that being technologically aware, human resource employees may perform their functions much easier.

It is reflected in **Table 3** that personal innovativeness has a significant positive relationship to artificial intelligence (PINN→AI) with a p-value of 0.006 (H4), at $p<0.05$. It can be gleaned that personal innovativeness affected by artificial intelligence is supported. In Duan et al. [64], AI has consistently been divisive and controversial, both within organizations and among individuals. However, it is becoming more widely acknowledged that decision-making can be greatly enhanced by artificial intelligence. Thus, it implies that artificial intelligence is helping employees for their personal innovativeness.

Table 3 presents a positive but statistically insignificant correlation between perceived risk and technological awareness (PR→TA; $p = 0.546$, $p > 0.05$) (H5). While this suggests a potential link, the current analysis lacks the power to definitively establish a relationship. The absence of significance does not negate the possibility of an influence; rather, it highlights limitations in the study's design to capture the subtle interplay between these variables. This finding resonates with the concerns expressed by Johnson et al. [65] regarding the potentially catastrophic consequences of uncontrolled AI development. Their cautionary perspective underscores the importance of further investigating the relationship between risk perception and technological awareness. To gain a more precise understanding, future research should incorporate more robust methodologies. This includes utilizing validated risk perception scales to provide a standardized measure of perceived risk, supplementing this with targeted items specifically addressing AI-related concerns (e.g., job displacement, algorithmic bias, data privacy) measured on a Likert scale. Qualitative data, gathered through open-ended questions, can provide valuable contextual insights into the nature of these perceived risks. Finally, sophisticated statistical analyses, such as regression modeling, should be employed to analyze the relationship between the comprehensively measured perceived risks and technological awareness, offering a more nuanced interpretation than the current non-significant finding. This enhanced approach will provide a more complete picture of how risk perceptions might shape the adoption and understanding of AI technologies.

The non-significant relationship between technological awareness and AI adoption (TA→AI; $p = 0.791$, $p > 0.05$) (H6) revealed in the study warrants further investigation. While the study highlights HR staff concerns regarding AI technologies—concerns that contrast with the widely documented potential benefits of AI in HR operations (as evidenced by numerous studies emphasizing AI's efficiency gains)—the lack of a significant relationship suggests a more complex reality. Several factors could contribute to this unexpected finding. Firstly, the existing technological awareness among participants may already be relatively high, rendering any additional influence from AI adoption negligible. Secondly, the study's design may not have adequately captured the nuances of AI integration within HR workflows. The mere use of AI-powered technologies does not necessarily equate to full utilization or understanding of their capabilities. Employees may be using AI tools superficially, without fully grasping their potential to enhance efficiency and effectiveness. Thirdly, organizational factors, such as a lack of supportive management practices, insufficient training, inadequate resources, or ethical concerns surrounding AI implementation, could hinder the effective integration of AI and thus mask any positive relationship between technological awareness and AI adoption.

Future research should delve deeper into these potential explanatory factors. This includes exploring the specific types of AI technologies used, the level of employee training and support, the organizational culture surrounding AI adoption, and the perceived ethical implications of AI in the workplace. By addressing these aspects, future studies can provide a more comprehensive understanding of the complex interplay between technological awareness and AI adoption within HR functions. A deeper understanding of these factors is crucial for developing effective strategies to leverage AI's potential while addressing employee concerns and mitigating potential risks.

Haenlein and Kaplan [66] conducted a study suggesting that AI technologies have the potential to enhance employee engagement and satisfaction. Through personalized learning experiences, career advancement prospects, and immediate feedback, AI can establish a workforce that is more motivated and involved. This is especially pertinent in the healthcare industry, where ongoing professional growth is essential. The research highlights that the effective integration of AI can result in a workforce that is more engaged, thereby dispelling the belief that awareness of AI technology does not impact HR operations. Thus, the researchers conclude that the results found are not supported but should be explored in studies to be conducted in the future.

Figure 5 and **Table 3** illustrate how the human resource functions of the Philippines' health sector are being impacted by artificial intelligence, specifically in the selected cities in Region 3 of the Philippines who participated. The variation reported in the aforementioned analysis, which used the SmartPLS method, was backed up by the *r*-square, which showed a round total of 53.8%. Conversely, the Philippines' human resource functions are affected by artificial intelligence, according to the bootstrapped model.

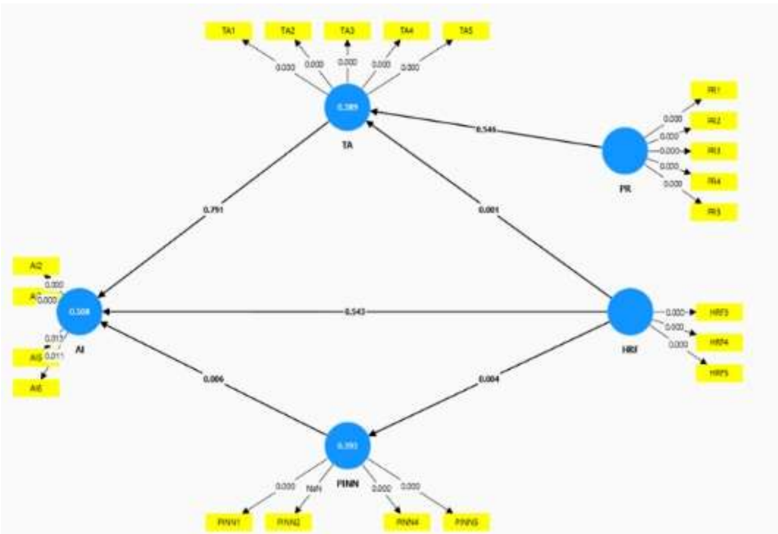

Figure 5. Bootstrapping model applied in the study

On the inner and outer arrows of **Figure 4**, respectively, are the *p*-values and *t*-values of the current study particularly in Region 3 of the Philippines. Based on the analysis, the effects of AI on human resource functions are positively influenced by the personal innovativeness and technological awareness of human resource employees.

4. Conclusions

The objective of the study is to determine whether there is a substantial connection among Technological Acceptance Model factors. Technological Acceptance Model was used to establish a framework for the study and explain how the variables were linked to one another.

This study utilized SmartPLS 4 for path analysis in order to test the hypotheses . Three of the nine hypotheses were significant and met the threshold of significance of $p>0.05$. The insignificant hypotheses implicate advantages of AI functions which do not directly influence the human resource employees. They are not yet ready to fully utilize the benefits of the artificial intelligence when it comes to their human resource functions. Nonetheless, the study can be used as a point of reference if anyone wishes to further pursue this topic.

The research findings revealed the relationship of the Technology Acceptance Model factors, namely: technological awareness and personal innovativeness were found significant. This significant result leads to an improved human resource function related task that may help human resource employees enrich their skills and knowledge, therefore improving the whole experience. This will help future employees to fit more to the much-needed additional manpower of any company that will adapt technological changes.

The results indicate that personal innovativeness and technology awareness have an effect on the relationship between AI and functions of human resource personnel. It also suggests that human resource professionals will find the advantages of incorporating artificial intelligence into human resource activities provided they have the proper mindset about technology awareness and personal innovativeness.

Table 4 below displays a summary of the trajectories of the hypotheses' trajectories, together with the corresponding *t*-statistics and *p*-values indicating their level of support or lack thereof.

Table 4. Path coefficients achieved

Hypothetical Path	*T*- Statistics	*P*- Values
H1: Human resource functions are correlated with Artificial Intelligence.	0.608	0.543
H2: Human resource functions are influenced by personal innovativeness.	2.876	0.004
H3: Human resource functions are influenced by technological awareness.	3.221	0.001
H4: Personal innovativeness is affected by Artificial Intelligence.	2.767	0.006
H5: Technological awareness has some implications of perceived risks.	0.604	0.546
H6: Artificial Intelligence influences technological awareness.	0.265	0.791

The summary shown in Table 4 includes three (3) hypotheses with $p<0.05$ and were determined to be substantial and accepted. Out of the six (6) hypotheses, H1, H5, and H6 were not supported, suggesting that artificial intelligence does not directly affect human resource functions. Perceived risk, as well as artificial intelligence, does not significantly impact technological awareness. This implies that participants have knowledge or awareness of artificial intelligence; they are not yet ready to fully adapt it in their workplace, but may still consider it in the future.

Nevertheless, these findings suggest that although human resource professionals recognize the potential advantages of artificial intelligence, they may not be fully ready to incorporate it into their roles. The results underscore the importance of nurturing personal innovativeness and technological awareness to facilitate a more appropriate use of artificial intelligence in the operations of human resource staff in this field.

4.1. Limitations

Firstly, the use of a cross-sectional survey restricts the ability to establish causal relationships, indicating that longitudinal studies could have offered more profound insights into the dynamics of these variables over time. Secondly, the online distribution of the survey resulted in a low response rate of 201 participants, which may not accurately represent the entire population. Moreover, the participants surveyed were limited to the gender binary (male and female), excluding non-binary or other gender identities.

4.2. Implications

This research study can serve as a benchmark for human resource professionals who are not fully capitalizing on the advantages of artificial intelligence. It offers valuable insights that can steer the improvement of human resource functions by embracing artificial intelligence. The findings underscore the important role of human resource practitioners to cultivate personal innovativeness and technological awareness in order to seamlessly integrate artificial intelligence into their operations. From an industry perspective, the conclusions of this study can be utilized to advocate for, promote, and raise awareness about new artificial intelligence technologies among human resource professionals most especially in the medical field.

In addition, embracing artificial intelligence has the potential to streamline and centralize human resource processes, thereby reducing workloads and increasing productivity. The study suggests that traditional methods can be augmented with artificial intelligence, resulting in more enjoyable and efficient day-to-day tasks for human resource practitioners.

4.3. Recommendations

The conclusions of this investigation can be applied to advocate for, promote, and create awareness of new technologies—particularly those that incorporate artificial intelligence -- to help healthcare practitioners stay updated with current trends in treating their clientele. Almost everybody knows that traditional methods still work; but with the help of artificial intelligence, everything seems to be organized, centralized, and systematized. It can reduce workload because of the streamlined process and the automation that artificial intelligence offers. Human resource practitioners can be more productive with less stress and their day-to-day task can be more enjoyable.

Future studies should maintain rigorous validation procedures while also considering qualitative findings to verify conceptual boundaries and measurement accuracy. Incorporating both qualitative and quantitative validation strategies can help capture the complexity of constructs in HR technology adoption research. A separate and in-depth qualitative investigation is recommended to explore the barriers to the adoption of artificial intelligence (AI) technologies in healthcare human resource (HR) practices. While the current study offers a foundational understanding of the impact and potential of technology adoption, it does not fully capture the underlying personal, cultural, institutional, and psychological factors that may hinder or delay the integration of AI in day-to-day HR operations. A qualitative approach—such as in-depth interviews or focus group discussions—can provide rich, contextual insights into the perceptions, apprehensions, and lived experiences of HR healthcare practitioners, thereby uncovering nuanced challenges that quantitative data alone may not reveal. The following may be done:

1. **Conduct Regular AI Literacy and Training Programs** – Equip HR staff with the knowledge and skills necessary to utilize AI tools effectively through continuous learning opportunities.

2. Foster a Culture of Innovation – Encourage a workplace environment where experimentation with AI tools is supported and innovation is rewarded.

3. Invest in Scalable AI Solutions – Choose AI platforms that are user-friendly and adaptable to the unique needs of healthcare institutions.

4. Engage Stakeholders in AI Planning – Involve both administrative and clinical HR professionals in decision-making to ensure alignment with organizational goals.

5. Monitor and Evaluate AI Performance – Implement performance metrics to track the impact of AI on HR efficiency, productivity, and employee satisfaction.

6. Ensure Ethical AI Use – Develop clear guidelines to ensure that AI use complies with ethical standards, data privacy laws, and patient confidentiality policies.

By implementing these strategies, organizations—especially those in the healthcare industry—can accelerate their digital transformation while maintaining the human touch essential to effective HR management.

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Conflict of interest

The authors declare no conflict of interest

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