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Impact of Practitioner Factors on Adoption of Human Resource Analytics in the Organizations of Nepal

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ABSTRACT

This study intends to explore the practitioner factors that influence the adoption of HR analytics in the developing country, Nepal. Adopting a quantitative approach to research and using a self-administered questionnaire, 385 organizations were purposively sampled from various types of organization in Nepal. IBM SPSS was used for analysis of the data. The empirical results exhibit that there is a statistically significant relationship between awareness and readiness of practitioners for adopting human resource analytics. However, IT expertise/analytical skills do not have a significant relationship with the same. The study concludes that organization must prepare employees for technological changes by clearly communicating the purpose and benefits of the new technology by conducting hands-on training sessions, offering step-by-step guides, and providing continuous support. These results contribute to theory by providing insights into how practitioner-related factors, such as awareness, IT expertise/analytical skills, innovation, and readiness influence the adoption of HR Analytics enriching existing models of technology adoption in the organizational context. From a regulatory perspective, the findings can inform policy frameworks to emphasize training, skill development, and standardized guidelines, ensuring organizations in Nepal are better equipped to adopt and implement HR analytics effectively.

Keywords: Analytical skills, developing countries, human resource analytics, practitioner readiness, technology adoption

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1. INTRODUCTION

Analytics in human resource management (HRM) is a relatively new notion, yet it has been around for a while. The concept of metrics and numbers in HR dates back to the early 1900s and the first book on the topic, how to Measure Human Resources Management, was released in 1984. After all these years, the question of why HR analytics is now so important to enterprises has arisen (Ejaz et al., 2020). Business executives and HR managers should start planning how to integrate HRA in their organisations. The focus of HR management should shift from transactional to strategic issues, with a focus on business impact rather than HR efficiency (Etukudo, 2019). Analytics are regarded as having the ability to revolutionise not only what HR does, but also how HR affects organisations (Fernandez & Gallardo-Gallardo, 2021). Adoption and implementation are also impacted by how well new and old IT work together. When information and data can be shared between IT systems without the need for human synchronisation, that compatibility is said to exist. The user experience is not harmed when new technology is introduced as part of a reform that is compatible with already existing technology; end users are spared from having to enter data again or produce new documents (Karp, 2014). For HR professionals to get a competitive edge, they must work in the measurement and analytics fields (Ejaz et al., 2020). The adoption of systematic methods in decision-making for HR has the potential to improve human-related decisions, much like how technical methods help marketers make educated decisions about the spending habits of their customers and finance departments in working capital forecasts (Shet et al., 2021).

The HRA uses a combination of expertise from the fields of information science, information technology, computer science, mathematics, and statistical science to analyses data in real-time and make data-driven results to forecast the consequences of complicated issues. Today, HR analytics is a powerful tool for progress; it uses current data to predict future ROI and is regarded as a source of essential value (Ekka & Singh, 2022). The implementation of HR analytics has proven to be a game-changer, allowing organizations to increase employee skills, retention, and acquire a competitive edge (van der Togt & Rasmussen, 2017). The importance of HRA lies in its ability to inform decisions related to recruitment, retention, performance management, and employee engagement, ultimately driving organizational efficiency and reducing costs (Deloitte, 2016). In developing countries like Nepal, HRA presents both challenges and opportunities. Challenges include a lack of awareness, technological barriers, inconsistent data quality, and a shortage of skilled professionals. However, as digital transformation accelerates, there are opportunities to adopt affordable HR tools, build capacity through training programs, and gain a competitive edge by improving HR practice (Nayyar et al., 2024). By embracing HR Analytics, organizations in Nepal can enhance workforce planning, measure HR initiatives' return on investment, and create data-driven strategies for sustainable growth. In the context of Nepal, it adopts a wide range of HR practices that are typical of western and developed nations. In order to effectively compete in regional markets, they also work to develop HRM systems that put them on par with multinational corporations while incorporating Nepali cultural traits (Gurung & Choi, 2019).

Adopting technical innovations is a complicated decision that depends on many people as well as societal factors. As a result, there is frequently a noticeable gap in time between the creation of a technology and its widespread user acceptance (Klein et al., 2019). Even though there has been a lot of study done and a variety of hypotheses put out to explain HR analytics in various adoption circumstances, several important concerns still need to be resolved.

This research aims to provide practitioners factors that influence adoption of HR analytics in the organizations of Nepal. The results of this study are anticipated to close a gap in the literature, particularly that linked to the application of HR analytics among HR specialists in Nepal.

2. LITERATURE REVIEW

Analytics that concentrates on metrics and measures connected to human operations is known as human resource analytics. It raises employee productivity and guarantees the amount of HR investment. It verifies all of the decisions made, from hiring to integrating new hires into the company. Making decisions based on data analysis is more likely to result in objective decisions than decisions based only on intuition (Alamelu et al., 2017). Baig et al. (2021) develop a model that will help determine the variables that affect BDA in the education sector. The results show that BDA is significantly influenced by human competence and talents. It is a crucial element that facilitates the BDA process. As a result, decisions regarding adoption may be postponed due to a lack of human expertise and abilities. A higher level of knowledge in a particular topic is referred to as expertise and skills, and it is typically learned or acquired. It requires significant, clear, and consistent effort on the part of the learner. Ramzi et al. (2021) discovered that HR professionals will employ HR analytics if they anticipate that doing so will involve less effort. Also, Fritz-Enz (2010) explained the lack of business intelligence and mathematical expertise among HR practitioners, as well as their inability to comprehend and deal with quantitative data, are some of the issues influencing the acceptability of innovations in HR. Musyaaffi et al. (2021) used the combination of the Technology Acceptance Model (TAM) 3 and Technology Readiness (TR) to examine the elements that influence users' adoption of e-banking. The results show that self-efficacy and technological preparedness both have a favourable impact on perceived usefulness, which in turn influences behavioural intention to adopt technology.

Nguyen et al. (2021) study shows that the top management's support, data security, partner pressure, and budgetary resources are the five most crucial variables in predicting readiness. In order to effectively allocate resources, integrate services, and rethink processes, top management support is essential for the use of big data. Again, the organization's readiness for BDA is greatly influenced by its IT infrastructure, security, top management support, size of the firm, and competitive advantage (Lasanthika & Wickramasinghe, 2020). In the study done by Ghasemaghaei (2019) on firms readiness to adopt big data analytics identified that both structural and psychological readiness are important to create value through big data analytics application. Also, analytical tools are more likely to be used by businesses when they continuously stay up to date with new IT developments and when they have an environment that supports new methods of using IT. According to Kristianto et al. (2012) the competitiveness of a manufacturing company is determined by how quickly it can adapt new technologies through effective leadership, alignment of the strategic and technical leadership roles, and managerial directives on the available production resources and capabilities. It offers a fresh way for thinkers to explain how technology is being adopted in a manufacturing organisation. Likewise, the study indicates that a leader's ability to inspire strategic flexibility and produce greater advantage is a key component. According to earlier study (Compeau & Higgins, 1995), self-efficacy is necessary for technology adoption because it is essential for using the system. Self-efficacy, according to Luarn and Lin (2005), is the confidence in one's abilities to carry out a task. Experience and knowledge in the use of technology will further increase confidence and reduce protective behaviour (Mulyani & Rachmawati, 2016). Kashada et al. (2016) seeks to analyse and explain how user awareness and other aspects related to awareness affect adoption in developing nations. The findings demonstrated that low user knowledge continues to be a major and significant factor in the low rate of adoption of decision support systems in developing nations.

Awa et al. (2015) explains the crucial elements of the T-O-E framework that set ERP software adopters apart from non-adopters. The study revealed that technical expertise, perceived compatibility, perceived values, security, and the firm's scale were important adoption-determining factors. The theoretical frameworks discussed are particularly relevant to Nepal due to its emerging economy status and evolving organizational practices. TAM highlights the importance of ease of use and usefulness to overcome resistance to change in organizations where HR analytics is a new concept. Technological readiness is vital as varying levels of digital literacy and technology readiness among organizations necessitate tailored strategies for adoption. Similarly, the T-O-E framework aligns with the challenges and opportunities in Nepal, where infrastructure limitations, skill gaps, and external pressures shape the adoption landscape. By integrating these models, the research can better identify the factors influencing HR analytics adoption and provide actionable recommendations for Nepalese organizations to embrace data-driven HR practices effectively. As per the best knowledge of current study researchers, most of the existing literatures are based on these theoretical frameworks but does not take in to consideration the factors which influence the intentions of practitioners for adoption of HR analytics in the organization. And very few studies are done in developing nations like Nepal. Hence, the present study fills this gap by studying the practitioner factors which affect the analytics adoption decision in the Nepalese organizations.

3. METHODS

This research is primarily based on quantitative research methods. The study considered all HR professionals in Nepal as the population. The total population size is not available. A sample of 385 HR professionals was selected from various organizations across Nepal using the purposive sampling method. The researchers have used purposive sampling technique because it allows to concentrate on relevant participants who have firsthand experience, expertise, or participation with HR analytics, it is especially helpful for discovering practitioner variables in the acceptance of HR analytics. HR practitioners who actively work with HR analytics were selected for the collection of data, similarly, the organization which has HR department and use analytics in decision making. A survey questionnaire was prepared for data collection, consisting of socio-demographic information and five-point Likert scale statements to measure various constructs, with options ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was developed with reference to previous literature and in consultation with experts. For data collection, the researchers and some enumerators personally visited the respondents and requested them to complete the questionnaire. This survey was conducted during the last six months of 2023. The research applies IBM SPSS AMOS software for analyzing the data. Both descriptive and inferential analysis are used in the study. Frequency distribution analysis is used for analyzing personal profiles of respondents, mean score analysis is used for analysis of measurement scale of practitioner factors and structural equation modelling (SEM) is applied to show the relationship between dependent and independent variables.

The reliability and validity of the measurement scales were assessed using various tests. Reliability was measured using Cronbach's alpha and Composite Reliability, where values above 0.70 were considered indicative of good reliability. Similarly, convergent validity was assessed using the Average Variance Extracted (AVE), with AVE values above 0.50 considered satisfactory. Discriminant validity was evaluated using Fornell and Larcker's criteria, where the square root of the AVE exceeding the correlation values between constructs ensured discriminant validity.

4. RESULTS AND DISCUSSION

4.1 Personal Profile of Respondents

Table 1 presents personal profile of respondents which includes gender, qualification, and type of the organization, numbers of years working in current organization, total experience as HR professional and whether the organization is fully or partially computerized.

Table 1

Personal Profile of Respondents

Particulars	Categories	Frequency	Percent
Gender	Male	227	59.0
	Female	152	39.5
	Not prefer to say	6	1.6
Qualification	Diploma	1	.3
	Bachelor	119	30.9
	Masters and above	265	68.8
Type of the Organization	Information Technology (IT)	48	12.5
	Manufacturing	56	14.5
	Banking and Financial Institutions	108	28.1
	Hospitals	38	9.9
	Hotels	31	8.1
	Automobiles	19	4.9
	Insurance	24	6.2
	others	61	15.8
Number of years working in current organization	1-5 years	156	40.5
	6-10 years	163	42.3
	11 years and above	66	17.1
Total experience as HR Professional	1-2 years	85	22.1
	3-5 years	144	37.4
	5 years and above	156	40.5
	Total	385	100

Table 1 revealed that 59 percent were male while 39.5 percent were female and 1.6 percent of them do not prefer to say their gender. The most of these respondents (68.8%) have a master's degree, while 30.9 percent have bachelor's degree. Likewise, the representation of organization comprised of banking and financial institutions (28.1%), others (15.8%), manufacturing (14.5%), IT (12.5%), hospitals (9.9%), hotels (8.1%), insurance (6.2%) and automobiles (4.9%). Similarly, majority of the respondents (42.5%) have worked for 6-10 years in the current organization while 40.5 percent of them have worked for 1-5 years and 17.1 percent have worked for above 11 years. Additionally, in terms of total experience as HR professional, 40.5 percent have above 5 years of experience, 37.4 percent have up to 3-5 years of experience and 22.1 percent have up to 1-2 years of experience.

4.2 Opinion towards Practitioners' Attributes and HR Analytics Adoption

The current study used 39 items to measure practitioners' attributes and HR analytics adoption. With options from 1 (strongly disagree) to 5 (strongly agree), a five-point Likert scale is used to measure the items. Table 2 displays the mean score analysis results.

Table 2

Mean Value Related to Practitioner's Attributes HR Analytics Adoption

Item Code	Statements	Mean	SD
AW1	Employees have the knowledge necessary to use the HR analytics	3.78	0.998
AW2	The organization provides enough guidance related to HR analytics.	3.6	0.87
AW3	Employees have received enough information about the benefits of using HR analytics.	3.69	0.97
AW4	Employees are familiar with the connection between data analytics and decision making.	3.53	0.966
AW5	Employees obtain knowledge from different sources: customers, partners, and competitors.	3.77	0.893
AW6	In general, employees know about HR analytics.	3.6	0.925
AW7	Employees easily identify data for analysis.	3.56	0.928
ITA1	Employees have sufficient technical knowledge to implement HR analytics.	3.51	1.063
ITA2	Employees have the ability to quickly learn and adopt innovation.	3.68	0.89
ITA3	Employees have the proficiency and information to maintain HR analytics.	3.7	0.961
ITA4	The organization's managers at different levels are IT literate.	3.62	0.979
ITA5	The employees in the organization have high levels of IT-related skills and technical knowledge.	3.53	0.992
ITA6	Employees know the business process well enough to identify the required applications.	3.58	0.921

ITA7	Employees have the ability in supporting HR analytics development.	3.69	0.964
ITA8	Within the organization employees have necessary skills to use HR analytics.	3.56	0.903
IN1	Other people come to us for advice on HR analytics.	3.16	1.138
IN2	HR practitioners can usually figure out new high-tech technologies without help from others.	3.3	1.034
IN3	Employees keep up with the latest technological developments in their areas of interest.	3.42	1.092
IN4	Employees enjoy the challenge of figuring out high-tech gadgets.	3.32	1.052
IN5	Employees of my organization have fewer problems than other organizations in making technology work for them.	3.42	1.065
IN6	Employees prefer to use the most advanced technology available.	3.55	1.065
IN7	Employees find new technologies to be mentally stimulating.	3.52	1.106
IN8	Learning about technology can be as rewarding as the technology itself.	3.54	1.036
IN9	Employees are open to learning about new and different technologies.	3.53	1.036
RS1	Employees have the right skills to work with HR analytics.	3.57	0.933
RS2	Employees understand how HR analytics can be used in my organization.	3.63	0.91
RS3	Employees are beginning to explore using HR analytics.	3.62	0.942
RS4	Employees are interested in using HR Analytics.	3.71	0.937
RS5	Employees are recommending the organization to invest in HR analytics	3.63	0.984
RS6	Employees use HR analytics for some specific tasks.	3.69	0.958
RS7	Learning to use HR analytics is easy for Employees.	3.6	0.99
HRA1	The organization is putting a policy in place to use HR Analytics.	3.88	1.071
HRA2	The organization is beginning to explore using HR analytics.	3.75	0.855
HRA3	Adoption of human resource Analytics system helps in strategic human resource management.	4.08	0.808
HRA4	The use of HR analytics is voluntary in organization.	3.56	1.054
HRA5	The organization is interested in using HR analytics.	3.86	0.865
HRA6	The organization uses HR analytics for some specific tasks.	3.7	0.94
HRA7	The number of business operations and activities in my company that requires HR analytics is high.	3.71	0.943
HRA8	Company is ready to adopt HR analytics in few months.	3.54	0.981
	Average mean	3.6074	

Note. N= 385, The scale value range from 1 (strongly disagree) to 5 (strongly agree).

Table 2 exhibit the items used to measure practitioners' factors and HR adoption in the organizations of Nepal. The study took four major measurable factors: awareness, IT expertise/analytical skills, innovation and readiness. The mean score value more than 3 indicates that HR professionals agrees with the statement. Based on the table, the first factor awareness has mean score value ranging from 3.5 to 3.7 which indicates that respondents have positive response towards awareness of HR analytics. Likewise, mean score of IT expertise/analytical skills range from 3.5 to 3.7 which means they agree that IT expertise/analytical skill is important for HR adoption. Similarly, the mean score of innovation ranges from 3.1 to 3.5 indicating HR professionals' positive response towards innovation. Also, the mean score of readiness ranges from 3.5 to 3.7 showing positivity towards readiness. Lastly, the item included in HR adoption has mean score value of 3.5 to 4.08 which demonstrates positive response towards HR adoption.

4.3. Structural Equation Modelling (SEM)

This comprises of measurement model and structural model. Measurement model evaluates the model fitness as well as constructs validity and reliability. Likewise, structural model examines the impact of different factors on HR adoption.

4.3.1. Measurement Model

Figure 1 depicts the measurement model and the result of model fit indicators are displayed in Table 3.

Table 3

Model Fit Indicators

Fit Indices	Criteria	Calculate value	Remarks
CMIN/DF	< 3	2.883	Good fit
GFI	0.9 or above	0.900	Good fit
NFI	0.9 or above	0.902	Good fit
CFI	0.9 or above	0.933	Good fit
RMSEA	< 0.08	0.07	Good fit

Table 3 presents the model fit indicators for the measurement model. The CMIN/DF value is 2.883, indicating a value lower than the threshold of 3, which suggests a good fit. Similarly, the GFI value is 0.900, the NFI value is 0.902, and the CFI value is 0.933, all of which exceed the threshold of 0.90, indicating a good fit. Additionally, the RMSEA value is 0.07, which falls below the cut-off of 0.08, further supporting a good fit for the model. In summary, these collective fit indices confirm that the model fits well with the data.

Figure 1

Measurement Model

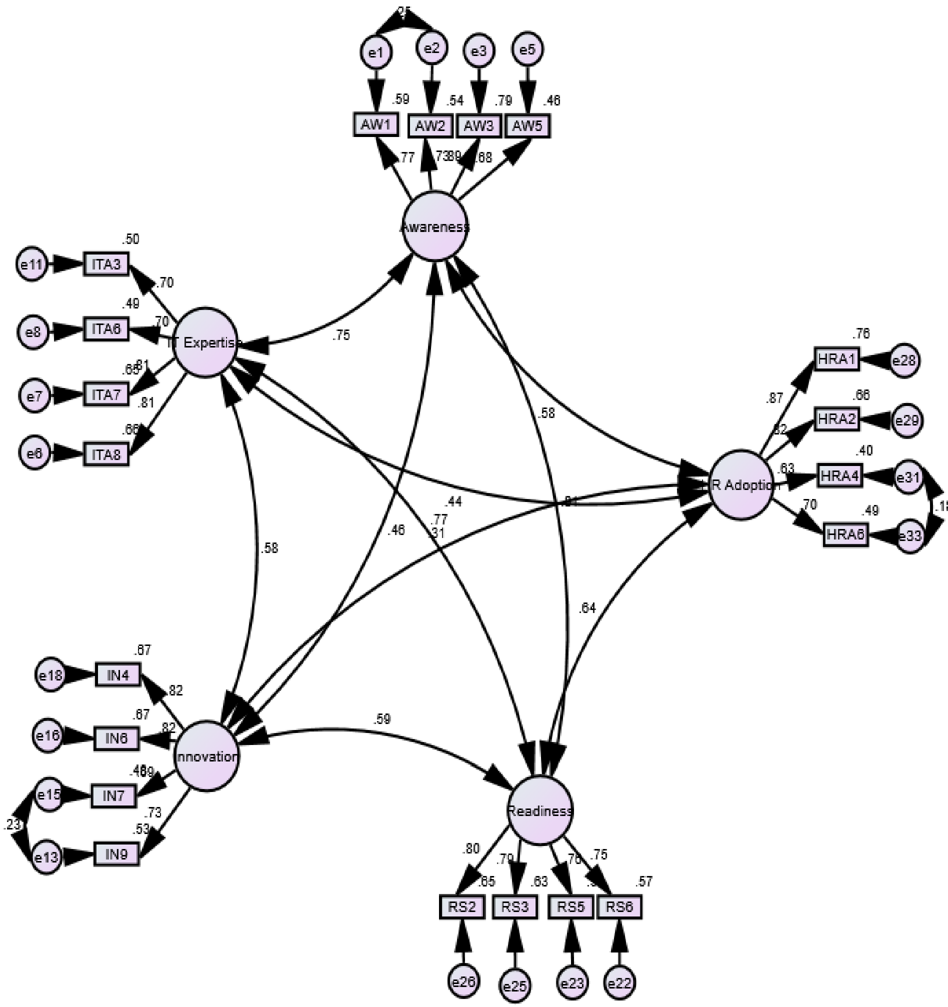

Table 4 displays the outcomes of a confirmatory factor analysis (CFA) along with reliability and validity tests conducted on five constructs within the measurement model. According to the table, all items of each construct exhibit loadings higher than 0.50 and are statistically significant at a 5 percent level of significance. Additionally, the Cronbach's Alpha and composite reliability values exceeding 0.70 indicate that all constructs are reliable. Furthermore, the AVE values surpassing 0.50 validate the convergent validity of the constructs. In summary, the table confirms the robustness and credibility of the measurement model based on these findings.

Table 4

Result of CFA, Reliability and Validity Test

Constructs	Items	Estimate	Critical Ratio	P-value	Cronbach's Alpha	Composite Reliability	AVE
Awareness	AW1	0.767	----	----	0.855	0.853	0.594
	AW2	0.734	16.806	***			
	AW3	0.888	17.348	***			
	AW5	0.678	13.224	***			
IT Expertise/ Analytical Skills	ITA3	0.705	14.371	***	0.841	0.843	0.575
	ITA6	0.702	14.3	***			
	ITA7	0.805	16.868	***			
	ITA8	0.813	----	----			
Innovative	IN4	0.819	14.393	***	0.858	0.85	0.589
	IN6	0.819	14.394	***			
	IN7	0.694	14.418	***			
	IN9	0.728	----	----			
Readiness	RS2	0.804	15.858	***	0.86	0.861	0.607
	RS3	0.794	15.633	***			
	RS5	0.763	14.976	***			
	RS6	0.754	----	----			
HR Adoption	HRA1	0.87	----	----	0.844	0.844	0.579
	HRA2	0.815	17.676	***			
	HRA4	0.634	12.85	***			
	HRA6	0.702	14.642	***			

Table 5

Discriminant Validity – Forenell Lacker's Criteria

	AW	IT	IN	RS	HRA
AW	***0.771***				
IT	0.747	***0.758***			
IN	0.465	0.581	***0.767***		
RS	0.708	0.678	0.594	***0.779***	
HRA	0.578	0.436	0.308	0.635	***0.761***

Table 5 displays the results of the discriminant validity assessment using the Fornell-Larcker's criteria. For each construct, the diagonal values (bold and italic) signify the square root of the average variance extracted (AVE) and the other values represent the correlations between them. As per the Fornell-Larcker's criteria, the square root of the AVE for each construct in the table is higher than its correlations with every other constructs. This ensures that the constructs have sufficient discriminant validity.

4.3.2 Structural Model

After evaluating the model fit, conducting reliability and validity tests, the researchers proceeded to run a structural model. Figure 2 illustrates the path diagram, visually representing the associations between the variables in the model. The output of the path diagram is presented in Table 6, which summarises the findings of the analysis, including the estimated coefficients, critical ratios, and p-values for each path.

Table 6 presents the findings regarding the impact of Awareness (AW), IT Expertise/Analytic skills (ITA), Innovative (IN), and Readiness (RS) on the HR Adoption (HRA) construct. The study reveals that Awareness have a favourable and statistically significant impact on HR Adoption, with a beta coefficient of 0.252, a critical ratio of 2.28, and a p-value of 0.023. Similarly, Readiness also have a positive and significant impact on HR Adoption, with a beta coefficient of 0.613, a critical ratio of 4.82, and a p-value of 0. The findings of the study align with

Figure 2

Path Diagram

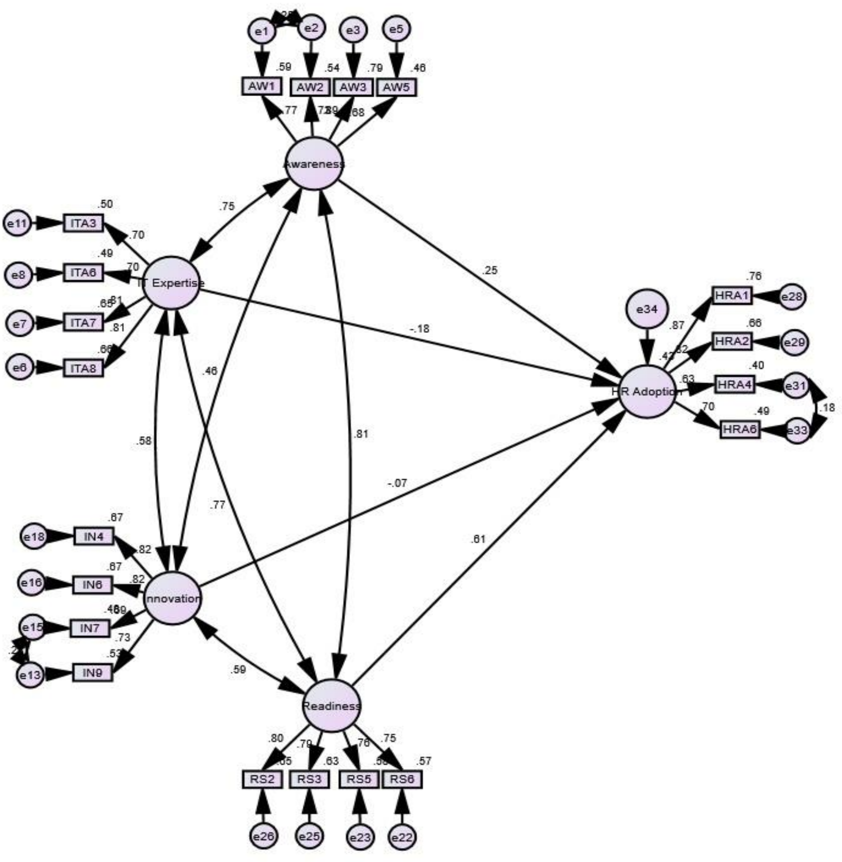

Table 6

Path Analysis

Impact	Estimate	S.E.	C.R.	P
HRA <--- AW	0.252	0.135	2.28	0.023
HRA <--- ITA	-0.185	0.129	-1.814	0.07
HRA <--- IN	-0.066	0.086	-0.945	0.345
HRA <--- RS	0.613	0.164	4.82	***

the previous study of (Akpan et al., 2022; Angrave et al., 2016; Gupta & George, 2016; Chen et al., 2017; Kamble et al., 2019; Liebe et al., 2016). On the other hand, the study finds that IT Expertise and Innovative do not have a significant impact on HR Adoption in the organizations of Nepal. These findings align with the study of (Ottow, 2016). While the study findings are in contrast with findings of (Berezina, 2021; López-Pérez et al., 2019; Napitupulu et al., 2018). The differences in the findings may be due to variations of respondents and study area. In summary, Awareness and Readiness positively influence HR Adoption, while IT Expertise/analytical skills and Innovative do not exhibit a significant impact in this context.

5. CONCLUSION

To remain competitive, a company must develop as a whole and make adjustments to its technology and processes in order to outperform its rivals. Organisations need to develop their ability to integrate new technologies and handle the difficulties that arise. To successfully deploy a technology change, a number of issues need to be effectively handled in order to prevent challenges with internal conflict or manageable employee resistance to the change. This study, therefore focus on identifying the practitioner factors which affect adoption of HR analytics in the organization. The study found that awareness towards HR analytics and readiness of practitioner has significant impact on acceptance of HR analytics in the organizations of Nepal. Whereas, IT expertise/analytical skills and innovation do not exhibit a significant impact in this context. The study concludes that organization must make employees aware about the technology they are using and make them ready to adopt the change by clearly communicating, providing proper training, guidance and knowledge. The present study has covered only four practitioner factors associated to adoption of HR analytics in the organizations of Nepal. Further research could be conducted by considering more variables like self-efficacy, access to data quality and data-driven decision making culture. and other organizational factors such as technological infrastructure, financial readiness and learning culture related to HR analytics adoption.

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