THE RELATIONSHIPS BETWEEN TECHNOLOGY ADOPTION, HR COMPETENCIES, AND HR ANALYTICS OF LARGE-SIZE ENTERPRISES The Relationships Between Technology Adoption, HR Competencies, and HR An...

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THE RELATIONSHIPS BETWEEN TECHNOLOGY ADOPTION, HR COMPETENCIES, AND HR ANALYTICS OF LARGE-SIZE ENTERPRISES

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ABSTRACT

Purpose: The aim of this study is to explore the organizational construct that have relationship to HR Analytics in large-size organizations that operate their businesses in Thailand.

Theoretical framework: Technology Adoption and HR Competencies are the two organizational constructs that are introduced in this study to examine their relationship with the HR Analytics.

Design/methodology/approach: The study adopts a confirmatory factor analysis to develop the structural equation model through data collection from large-size organizations in Thailand.

Findings: The hypotheses of the proposed conceptual framework are confirmed at significant level of $p < 0.01$. In addition, the study also provided statistical confirmation of the role of Technology Adoption as a mediating factor of HR Competencies to HR Analytics.

Research, Practical & Social implications: The study gives the results to support the call from many authors around the area of HR Analytics and its influence on organization management.

Originality/value: The study offers pioneer views on the relationship of relevant organizational dimensions to the HR Analytics and helps to bridge the gaps on the existing studies.

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AS RELAÇÕES ENTRE ADOÇÃO DE TECNOLOGIA, COMPETÊNCIAS DE RH E ANÁLISE DE RH DE EMPRESAS DE GRANDE PORTE

RESUMO
Objetivo: O objetivo deste estudo é explorar a construção organizacional que tem relação com a HR Analytics em organizações de grande porte que operam seus negócios na Tailândia.
Estrutura teórica: Adoção de Tecnologia e Competências de RH são as duas construções organizacionais que são introduzidas neste estudo para examinar sua relação com os Analíticos de RH.
Projeto/método/abordagem: O estudo adota uma análise fatorial de confirmação para desenvolver o modelo de equação estrutural através da coleta de dados de organizações de grande porte na Tailândia.

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Conclusões: As hipóteses da estrutura conceitual proposta são confirmadas a um nível significativo de p < 0,01. Além disso, o estudo também forneceu confirmação estatística do papel da Adoção de Tecnologia como fator mediador das Competências de RH para a Análise de RH.
Pesquisa, implicações práticas e sociais: O estudo dá os resultados para apoiar a chamada de muitos autores em torno da área de Análise de RH e sua influência na gestão da organização.
Originalidade/valor: O estudo oferece visões pioneiras sobre a relação de dimensões organizacionais relevantes para a Analítica de RH e ajuda a preencher as lacunas dos estudos existentes.

Palavras-chave: Adoção de Tecnologia, Competências de RH, Analítica de RH, Grandes Empresas, Tailândia.

LAS RELACIONES ENTRE LA ADOPCIÓN DE TECNOLOGÍA, LAS COMPETENCIAS DE RRHH Y LA ANALÍTICA DE RRHH DE LAS GRANDES EMPRESAS

RESUMEN
Propósito: El objetivo de este estudio es explorar el constructo organizativo que tiene relación con HR Analytics en organizaciones de gran tamaño que operan sus negocios en Tailandia.
Marco teórico: La adopción de tecnología y las competencias de RRHH son los dos constructos organizativos que se introducen en este estudio para examinar su relación con HR Analytics.
Diseño/metodología/enfoque: El estudio adopta un análisis factorial confirmatorio para desarrollar el modelo de ecuaciones estructurales mediante la recopilación de datos de organizaciones de gran tamaño de Tailandia.
Resultados: Las hipótesis del marco conceptual propuesto se confirman a un nivel significativo de p < 0,01. Además, el estudio también confirmó estadísticamente el papel de la adopción de tecnología como factor mediador entre las competencias de RRHH y el análisis de RRHH.
Investigación, implicaciones prácticas y sociales: El estudio aporta los resultados para apoyar el llamamiento de muchos autores en torno al área de HR Analytics y su influencia en la gestión de las organizaciones.
Originalidad/valor: El estudio ofrece puntos de vista pioneros sobre la relación de las dimensiones organizativas relevantes con el HR Analytics y ayuda a cubrir las lagunas sobre los estudios existentes.

Palabras clave: Adopción de Tecnología, Competencias de RRHH, HR Analytics, Grandes Empresas, Tailandia.

INTRODUCTION

One of the necessary strategies for all businesses in driving organizational effectiveness is the transformation of HR's role into a value-added function. The reason for this is that HR is frequently perceived as failing to play a strategic role in developing and implementing organizational strategies, as well as failing to meet the expectations of becoming a strategic partner (Lawler, 2003). Strategic HR management has not yet utilized data to drive business decisions; thus, analytical decision-making is defined as a necessary capability for HR transformation. In comparison to some other corporate support functions like finance and marketing, HR seems to lack the analytical capability and, as a result, the analytical models to confirm the relationship of HR outcomes to organization effectiveness (Lawler et al., 2004). Google, Best Buy, P&G, and Sysco have taken the guesswork out of employee management by leveraging analytics to improve attracting and retaining talent by connecting employee data to business performance (Davenport et al., 2010). The emergence of new technology, such as big data, has influenced the transformation of many functions in an organization, including the human resources function. HR Analytics (HRA) reflects the need for this disruptive technology to transform the way organizations work around their people (Yoshikawa et al., 2020; Maçada et al., 2021). According to Marler and Boudreau (2017), HRA involves the use of technologies and statistical techniques to interpret employee data and create business insights from a people perspective. Bassi (2011) points out that HRA is an integration of methodology and process for quality improvement with respect to people-related decision making to better individual and/or organization performance. As a matter of fact, many studies have been conducted globally trying to confirm the impact of HRA on organizational performance in various business aspects. Although HRA is a hot topic being researched globally and regionally by HR practitioners and researchers, very little supporting evidence has been found to confirm that it is widely practiced in Thailand, which creates curiosity for the researcher to study its influencing factors and to answer the calls from various authors. Further research is needed to better evaluate the impact of these factors and investigate different components of its adoptions and implications (Kremer, 2018; Peeters et al., 2020; Marler and Boudreau, 2017; Sharma and Sharma, 2017). Therefore, this study aims to provide the contribution to the previously researches on the relationship of HRA to other relevant organizational management factors.

LITERATURE REVIEW

According to CIPD (2020), HRA is classified into three main capabilities. First, descriptive analytics is the use of descriptive data to illustrate aspects of HR work, for example, recording absence, annual leave, and attrition and recruitment rates. Second, predictive analytics—the use of data to predict future trends—can help HR professionals plan for future events and scenarios and ensure they are able to deliver to the business. Third, prescriptive analytics is an application of mathematical and computational sciences to suggest decision options that take advantage of the results of descriptive and predictive analytics.

Fosso Wamba et al., (2018) suggest that information quality and technology quality define the quality of big data analytics (BDA). An organization with robust technology can establish a good-quality information ecosystem that supports analytical activities. For instance, a company may produce more complete information by combining data from multiple sources that allow it to construct customer insights. As reviewed by Fernandez and Gallardo (2020), all authors agree that the quality of the raw material (data) heavily impacts the results of HRA. The full potential of HRA only works when reliable data comes from various sources both inside and outside the organization (Kremer, 2018).

Pillai and Sivathanu (2020) argue that technology integration and standardization are related to new technology applications. Technologies implemented in an organization should allow integration of information systems among hardware, software, mobile apps, websites, and artificial intelligence technology (AIT). The technology that enables an individual to perform tasks should also ease activities in other departments. Minbaeva (2017) suggests that investment in data management is necessary for an organization to stay away from complex and fragmented systems.

Singh and Singh (2019) suggest that Big Data Analytics (BDA) capabilities enable firms to create actionable business intelligence from a multitude of data sources. IT Infrastructure Capabilities (ITIC) play an important role for the firm in developing tools and capabilities related to BDA. It enables the firm to develop actionable business information through BDA. Therefore, enhancing ITIC is strategically focused, especially among technology-driven firms, to develop BDA capabilities.

Based on above literature reviews, this study proposed the following hypothesis:

H1: Technology Adoption have positive influence on HR Analytics

According to Vargas et al. (2018), understanding of technology is a top challenge for HR professionals. The HR practice made possible by information technology establishes business effect and enables data-driven decision-making using data on HR processes, human capital, organizational performance, and external economic benchmarks (Dahlbom at el., 2019). Many technology vendors offer HR software with embedded analytical capabilities and features to integrate with other business data. HR must be able to evaluate its benefits in comparison to other software or even the existing one (Kremer, 2018). Various types of technologies may be required to gather data, translate it into insightful workforce analysis, and then use those insights to inform strategic decision-making. Thus, HR analysts require in-depth knowledge of human resource information technology and an understanding of business intelligence tools such as Microsoft Excel, Tableau, and Power BI (McCartney et al., 2020). Even though many leading software development firms provide analytic packages, organizations should consider software with a user-friendly interface (Fernandez and Gallardo, 2020).

Based on above literature reviews, this study proposed the following hypothesis:

H2: HR Competencies have positive influence on Technology Adoption

Instead of merely validating pre-existing knowledge, HRA focuses more on asking the right business questions to add value and inform how to make business decisions that intervene and result in business success (Rasmussen and Ulrich, 2015; Kremer, 2018). Business partners typically have many of these value-added issues to discuss and support actionable HRA, but practitioners always start with business concerns that may not be possible to uncover purely by

HR (Minbaeva, 2017). HR analysts must be knowledgeable about business operations, management techniques, and overarching corporate goals in addition to having a fundamental understanding of HR procedures, such as recruiting and selection, compensation, employee and labor relations, and training and development (McCartney et al., 2020).

The analytics skill is the future wave of HR; by analyzing HR-critical data, an organization will be able to determine its future not only in the HR aspect but the business as well (Rasmussen and Ulrich, 2015). Although HR recognizes the importance of analytics, it is still a skill that many of today's HR professionals lack (Kremer, 2018). Analytics does not necessarily require the development of a sophisticated model if the analyst understands the business objective and how to analyze data; successful HRA can sometimes just be a simple correlation model (Minbaeva, 2017). Data fluency and data analysis are the outlines of the technical knowledge required by HR analysts to effectively utilize workforce data for analysis in generating statistical and analytical reports (McCartney et al., 2020). In addition to analytics skills, HR professionals invest in developing consultative skills along with analytics skills to facilitate all stakeholders in proper change management (Minbaeva, 2017). HR analysts require a wide range of consulting skills, including the ability to offer insights, recommendations, and strategies to various stakeholders based on analyzed workforce data to overcome organizational challenges (McCartney et al., 2020). HRA work is frequently presented in an academic style that is difficult for business audiences to understand. If its implications and recommendations cannot be explained in a single slide, there is a good chance that the work will not be accepted by executives (Rasmussen and Ulrich, 2015). To convert analytics into actionable business initiatives, effective storytelling that compiled reasons to persuade audiences was required (Minbaeva, 2017). Storytelling and communication skills are the focuses of HR analysts' ability to effectively translate workforce insights into compelling stories and convey the key messages to stakeholders and senior leadership (McCartney et al., 2020).

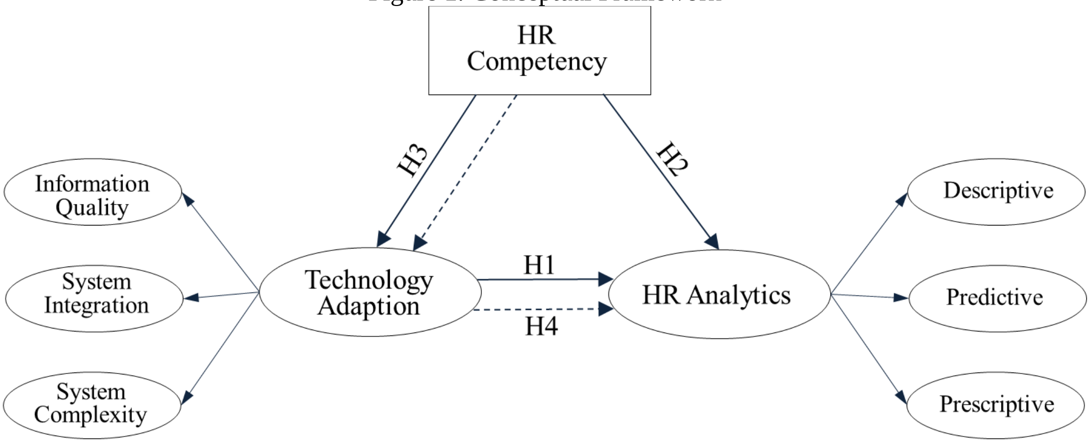
Based on above literature reviews, this study proposed the following hypothesis:

H3: HR Competencies have positive influence on HR Analytics

H4: HR Competencies have positive influence on HR Analytics through moderating effect from Technology Adoption

As summarized in Figure 1, is the conceptual framework of this study.

Figure 1. Conceptual Framework



Remark: the dotted line represents moderating relationship

METHERIAL AND METHODOLOGY

This study applied purposive sampling methodology to collect the survey responses from management-level employees working in human resources for large organizations, which are defined by RD (2021) as having an annual revenue of more than 500 million baht. With help from the Personnel Management Association of Thailand, 429 members from different organizations were chosen as the respondents with coverage in various industry, for example, financial, real estate, retail, hospitality, and manufacturing. The data collection process takes place during August to October of 2022 through the digital questionnaire ("Google Form"). There are altogether three parts for the questionnaire.

The first part, personal information, captures general characteristics of the respondents. Examples of the questions are gender, age, educational background, and work experiences.

The second section, organizational information, contains descriptions of the representative organizations. The questions include the following: revenue's range, employee's range, type of business, parental type of organization, and ownership type of organization.

Third, the relationship section was assessed using a questionnaire adapted from previous research. The questions to measure Technology Adoption are developed from the previous research, such as Mishra et al. (2018), Fosso Wamba et al. (2018), Lai et al. (2018), Rao et al. (2015), Kremer (2018), and Ren et al. (2016). The questions to measure HR Competencies are developed from the previous research, such as Verma et al. (2021), Jeble et al. (2018), Fernandez and Gallardo (2020), Mishra et al. (2018), Fosso Wamba et al. (2018), Minbaeva (2017), and Kremer (2018). The questions to measure HR Analytics are developed from the previous research, such as Minbaeva (2017), Fernandez and Gallardo (2020), CIPD (2018a), CIPD (2018b), Kremer (2018), Verma et al. (2021), and Dahlbom et al. (2019). In this section, the questionnaire is measured through a 5-point Likert scale (1-Strongly Disagree and 5-Strongly Agree) with reference interpretation of scale from Nyutu et al. (2021)

The analysis starts by exploring the normality of the data using SPSS v.23 and testing the results of mean, standard deviation, skewness, and kurtosis. According to Brown (2006), skewness and kurtosis help identify if a curve is normal or abnormally shaped. Acceptable values of skewness fall between -3 and + 3, and kurtosis is appropriate in a range of -10 to +10 when utilizing SEM. Thus, both values in this study fall into the acceptable range.

The Structural Equation Model (SEM) was applied to analyze the proposed conceptual framework by using LISREL 8.8. To measure the strength of a relationship of the observed variables to the latent variable, R-squared (R^2) or coefficient of determination is used to interpret the results. According to Moore et al. (2013), the value of 0.3 or greater is acceptable for researching purpose. In addition, convergent and discriminant analysis were conducted to adjust the model's fitness.

To perform convergent analysis, Factor Loading and Average Variance Extracted (AVE) were introduced as the measurements. Factor Loading is used to indicate the correlation coefficient for the variable and factor, the higher value represents that factor extracts sufficient variance from that variable. A rule of thumb in SEM is the value 0.5 or greater. Average Variance Extracted (AVE) is used to measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error. Fornell and Larcker (1981) suggests 0.5 as an acceptable value. To make the analysis more comprehensive, the researchers also analyze Composite Reliability (CR) and Cronbach's alpha. Composite Reliability (CR) is used to assess the level of reliability of the model by examining its factors loading. The expected measure is above 0.6 (Hair et al., 2010). Cronbach's alpha is a measure that applied to measure internal validity and consistency of the items of each observed variable. From literature reviews, the indicative value of greater than 0.3 is proposed as acceptable criteria for item-total correlation (Mokkink et al., 2010, Tavakol & Dennick, 2011). For discriminant validity, the square root of the AVE of each construct versus its correlation with the other.

To evaluate the role of Technologies Capabilities in moderating the impact of HR Competencies to HR Analytics, the statistical analysis of direct, indirect, and total effect is applied.

RESULTS AND DISCUSSION

From data cleansing process, 89 responses needed to be taken out because of data impletion, the final remain of 400 from 489 responses (80%) are in good quality to be proceeded further. Based on preliminary analysis to examine no multicollinearity of the data, the values of VIF for all items in the study are within the acceptable range (below 5.0) and the values of tolerance less than 0.1 (Kline, 2015). The distribution of data is normally distributed, and all items' factor loadings meet the 0.5 threshold, indicating that they are acceptable, and no items need to be removed.

As represented in Table 1, is the results of convergent validity.

Table 1 Convergent Validity

Construct	**Factor Loading**	**R^2**	**AVE**	**CR**	**Cronbach's alpha**
Information Quality	0.827	0.684	0.626	0.835	0.837
System Integration	0.869	0.755	0.695	0.872	0.867
System Complexity	0.803	0.646	0.635	0.835	0.800
HR Competencies	-	-	0.628	0.893	0.886
Descriptive	0.846	0.716	0.763	0.906	0.898
Predictive	0.806	0.650	0.766	0.908	0.899
Prescriptive	0.853	0.728	0.688	0.869	0.885

Source: Prepared by the authors (2022)

Table 2 shows the values of square root of AVE of each contract against its correlation to other contract, thus, all the values are higher than their comparative correlation. Supplementary with the result from Table 3, the crossloadings analysis also confirmed the same.

Table 2 Discriminant Validity

Construct	Information Quality	System Integration	System Complexity	HR Competencies	Descriptive	Predictive	Prescriptive
Information Quality	**0.791***	-	-	-	-	-	-
System Integration	0.718	**0.833***	-	-	-	-	-
System Complexity	0.663	0.700	**0.797***	-	-	-	-
HR Competencies	0.443	0.522	0.443	**0.792***	-	-	-
Descriptive	0.445	0.436	0.435	0.548	**0.874***	-	-
Predictive	0.362	0.406	0.369	0.544	0.682	**0.875***	-
Prescriptive	0.422	0.425	0.394	0.566	0.620	0.709	**0.830***

Source: Prepared by the authors (2022), *Square root of the AVE.

Table 3 Crossloadings

Item	Information Quality	System Integration	System Complexity	HR Competencies	Descriptive	Predictive	Prescriptive
inq1	**0.802**	0.608	0.582	0.411	0.416	0.330	0.403
inq2	**0.823**	0.674	0.581	0.347	0.366	0.313	0.349
inq3	**0.746**	0.588	0.568	0.402	0.377	0.299	0.347
sti1	0.674	**0.801**	0.572	0.415	0.389	0.381	0.368
sti2	0.603	**0.828**	0.634	0.442	0.343	0.371	0.365
sti3	0.638	**0.870**	0.661	0.533	0.430	0.332	0.400
stc1	0.584	0.663	**0.879**	0.439	0.415	0.323	0.330
stc2	0.508	0.439	**0.580**	0.283	0.327	0.297	0.306
stc3	0.593	0.681	**0.892**	0.406	0.362	0.316	0.365
hrc1	0.339	0.422	0.306	**0.726**	0.342	0.378	0.381
hrc2	0.488	0.518	0.473	**0.850**	0.487	0.424	0.457
hrc3	0.331	0.358	0.293	**0.727**	0.458	0.470	0.503
hrc4	0.338	0.427	0.371	**0.818**	0.496	0.500	0.515
hrc5	0.344	0.446	0.400	**0.831**	0.485	0.481	0.483
des1	0.390	0.397	0.405	0.494	**0.868**	0.597	0.563
des2	0.419	0.397	0.425	0.512	**0.886**	0.612	0.570
des3	0.412	0.401	0.359	0.497	**0.867**	0.664	0.565
prd1	0.283	0.294	0.314	0.484	0.610	**0.867**	0.637
prd2	0.358	0.443	0.364	0.511	0.642	**0.889**	0.659
prd3	0.350	0.375	0.331	0.495	0.615	**0.870**	0.643
prs1	0.400	0.388	0.375	0.503	0.571	0.644	**0.831**
prs2	0.357	0.403	0.354	0.547	0.565	0.647	**0.837**
prs3	0.382	0.361	0.336	0.484	0.541	0.628	**0.821**

Source: Prepared by the authors (2022)

As displayed in Table 4, is the results of direct, indirect, and total effect of the adjusted model. The R^2 of both Technology Adoption (0.325) and HR Analytics (0.506) pass the threshold value at 0.3. All three direct effects and the indirect effect of HR Competencies to HR Analytics (through mediating impact of Technology Adoption) are significant at $p < 0.01$.

Table 4 The Results of Direct, Indirect and Total Effect of the Structural Equation Model

Latent Variable / R^2	Technology Adoption			HR Analytics		
	DE	IE	TE	DE	IE	TE
HR Competencies (T-values)	0.570** (11.571)	-	0.570** (11.571)	0.481** (9.076)	0.243** (5.260)	0.724** (13.635)
Technology Adoption (T-values)	-	-	-	0.318** (5.734)	-	0.318** (5.734)
R^2	0.325			0.506		

Remark: DE = Direct Effect, IE = Indirect Effect and TE = Total Effect
* Significant at =/>1.960 and =<2.575 (Level = 0.05), ** Significant at >2.575 (Level = 0.01)

As proven through structural equation model in Figure 2 and Table 5, the researchers can summarize the result of hypotheses testing as below:

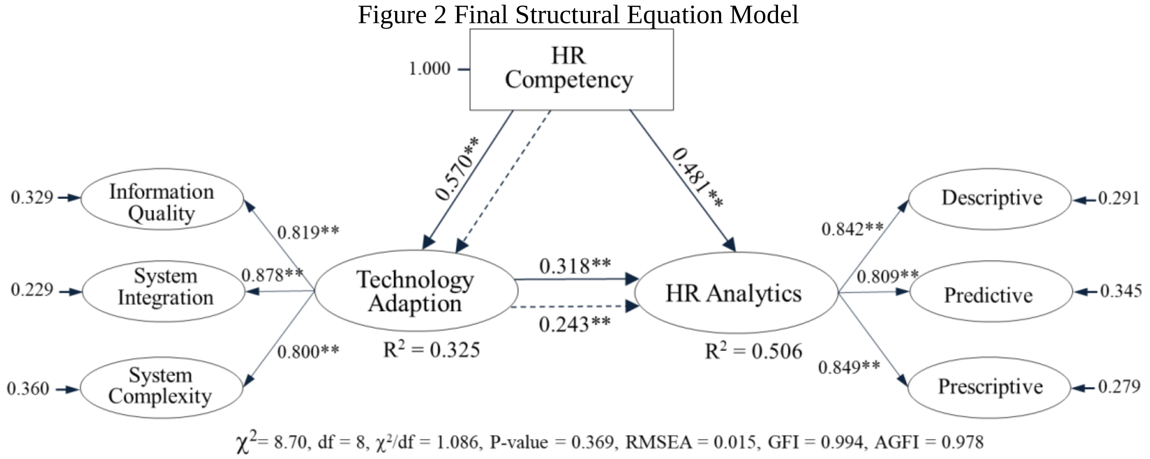
Hypothesis 1: Technology Adoption have positive influence on HR Analytics (ß = 0.213**, $p < 0.01$).

Hypothesis 2: HR Competencies have positive influence on Technology Adoption (ß = 0.418**, p < 0.01).

Hypothesis 3: HR Competencies have positive influence on HR Analytics (ß = 0.570**, p < 0.01).

Hypothesis 4: HR Competencies have positive influence on HR Analytics through moderating effect from Technology Adoption (ß = 0.243**, p < 0.01).

Figure 2 Final Structural Equation Model



Remark: the dotted line represents moderating relationship

Table 5 The Results of all observed and latent variable from the Structural Equation Model

Dimension	Observe/Latent Variable	Factor Loading/ Path Coefficient	SE	T-values	R^2
Lambda - Y	INQ <= TEA	0.819	-	-	0.671
	STI <= TEA	0.878	0.036	18.957	0.771
	STC <= TEA	0.800	0.034	17.423	0.640
	DES <= HRA	0.842	-	-	0.709
	PRD <= HRA	0.809	0.049	14.471	0.655
	PRS <= HRA	0.849	0.053	13.560	0.721
Beta	TEA => HRA	0.318	0.055	5.734	-
Gamma	HRC => TEA	0.570	0.066	11.571	0.325
	HRC => HRA	0.481	0.071	9.076	-
Gamma - Beta	HRC=>TEA=>HRA	0.724	0.065	13.635	0.506

Source: Prepared by the authors (2022)

It was confirmed in this study that both Technology Adoption and HR Competencies play important role in existence of HR Analytics in an organization. By looking at the level of impact among these two constructs, HR Competencies has stronger positive influence on HR Analytics than Technology Adoption (T-values = 9.076 and 5.734, respectively). However, if considering the relationship of all three constructs together, the strongest relationship is HR Competencies to Technology Adoption (T-values = 11.571). Lastly, this study also confirmed that Technology Adoption acts as the moderator in facilitating the impact from HR

Competencies to HR Analytics (T-values = 13.635). Thus, improvement of Technology Adoption and HR Competencies will lead to better practices in HR Analytics in large-size organizations.

CONCLUSION

The scope of this study conducted in Thailand, the results may vary from the studies conducted in different geographical regions. In addition, there are also some other organization factors that can be further examine the relationship to HRA. Future research should consider these two limitations to provide additional viewpoints.

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