Design thinking: a cognitive resource for improving workforce analytics and training evaluation

Zafar, Natasha; Asadullah, Muhammad Ali; Ul Haq, Muhammad Zia; Siddiquei, Ahmad Nabeel; Nazir, Sajjad

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Abstract

Purpose – The firms use training evaluation practices (TEPs) to determine the return of billions of dollars spent on employee training and development activities. The firms need to modernize the set of TEPs for evidence-based workforce management decisions. This study examines a mediation mechanism to explain how HR professionals' design thinking (DT) mindset strengthens the set of TEPs using predictive workforce analytics (PWAs).

Design/methodology/approach – We employed SPSS computational named MLMED to test the proposed relationships by collecting data from 180 management professionals serving in subsidiaries of Multinational corporations in Pakistan.

Findings – The statistical results demonstrated that DT is not directly related to firms' TEPs. However, the statistical results supported the mediating role of firms' use of PWAs between DT and TEPs.

Originality/value – The findings offer a new perspective for firms to use HR professionals' DT mindset for modernizing the set of existing HR practices

Keywords: Human Resource Management (HRM), Human Resource Strategies, Training, Design Thinking, Predictive Workforce Analytics

1. Introduction

Organizations invest huge time, money, and effort in employee training and development to increase organizational productivity, yet the consequences of these interventions always remain inconclusive and ambiguous (Diana & Katok, 2006). Training evaluation is a continuous process used by HR professionals to determine training efficacy (Asadullah et al., 2018; Brown, 2002). They use TEPs to strategically link training with organizational strategy and objectives (Martinez & Stuart, 2011). Training evaluation is an expository but complex HR practice to ascertain the effect of training interventions on individual and corporate performance (Flesher, 2007). Training evaluation is essential for HR professionals to justify the training investment in achieving its outcomes (D'Netto, Bakas, & Bordia, 2008). Some scholars and practitioners believe that evaluating training is the only way to influence human performance development efforts (Phillips, 2012; Phillips & Phillips, 2016). TEPs communicate to stakeholders about the increase in productivity resulting from training interventions (Guerci & Vinante, 2011).

Due to significant financial investment in training interventions, the organizational members have started questioning the effectiveness of TEPs to improve solutions (Ho, Arendt, Zheng, & Hanisch, 2016). They have mainly severe concerns about the maturity of TEPs concerning the latest technological advancements (e.g., big data, artificial intelligence, predictive analytics). Most practitioners believe that TEPs are outdated since they do not track real-time performance to provide timely feedback and opportunities for employees to improve their performance (Asadullah et al., 2018; Hung, 2010). They look for structural changes in the existing TEPs to bring more transparency (Kogan et al.,2018). Business leaders utilize fair training evaluation processes to determine the financial outcomes of recent training interventions and forecast future training investment outcomes (Lindzon, 2016; Thanrenou, Saks, & Moore, 2007). Hence, there is a dire need for updated TEPs based on modernized perspectives of thinking and the latest analytical tools and techniques (Levenson, 2011). There is a challenge for training evaluation professionals to address organizational members' concerns about the maturity of TEPs, evaluate the financial outcome of existing training interventions, and predict the results of future training interventions. Training evaluation professionals need to modernize their thinking to improve their training evaluation capabilities (Levenson, 2011).

DT appears to be the best technique for training evaluation professionals to face training evaluation challenges (Liedtka, 2017). DT is a human-centric and iterative approach for problem-solving (Cross, 2011; Liedtka & Ogilvie, 2011; Martin, 2009) that instigates dissatisfaction with the current situation, arises the need to change, offers a solution for the relevant problems, and involves feedback for future improvements (Dorst, 2011). We argue that the dissatisfaction of organizational members with the current set of TEPs requires training evaluation professionals to enhance the understanding of DT in TEPs currently used by training evaluation professionals. Unfortunately, the existing research has ignored the role of DT in TEPs despite its various positive organizational outcomes reported in the current literature (Dorst, 2011; Leavy, 2012; Chang, Kim, & Joo, 2013). This study used a resource-based view (RBV) of the firm (Barney, 1991; Batt, 2002) to contribute to this line of inquiry by investigating the role of DT in the set of TEPs used by training evaluation professionals in subsidiaries of multinational corporations (MNCs) in Pakistan.

This study offers another theoretical contribution by enhancing the understanding of DT in the set of PWAs used by human resource management (HRM) professionals. PWAs goes beyond a mere collection and analysis of data; instead, they appear as a holistic approach to predicting HR initiatives' quantitative outcomes for making future workforce decisions

(Chadwick, Super & Kwon, 2015). They assist organizational members in measuring workforce outcomes to make workforce decisions that improve the efficiency and effectiveness of the company (Ringo, 2012; Chornous & Gura, 2020). We believe that DT might be useful for human resource management professionals to design a more sophisticated set of PWAs for making various workforce decisions. However, existing research fails to offer any empirical evidence about human resource management professionals' role in the background of PWAs. Drawing on RBV, this study provides its primary contribution to the existing stream of research on TEPs to explain why some firms use more sophisticated TEPs. This study proposes that the firms may use a more sophisticated set of TEPs based on the DT mindset of their HR professionals that encourages them to use PWAs to improve workforce management decisions.

PWAs is a comprehensive construct involving predictive analytics about human resource management functions, including human resource planning, recruitment, selection, training and development, appraisal, and performance management (Malisetty, Archana, & Kumari, 2017). Training evaluation is a small part of workforce analytics (Sarivastava & Mohsin, 2020). Hence, this study proposed that organizations using a sophisticated set of PWAs may also design a better group of TEPs. Therefore, this study investigated the positive relationship between the sets of PWAs and TEPs used by the organizations. The existing research has neglected the positive relationship between a modernized set of PWAs and the set of TEPs used by subsidiaries of MNCs operating in Pakistan.

Finally, this study has advanced existing research on training evaluation by investigating the mediating role of PWAs between DT and TEPs. The companies benefitting from the DT approach use a more sophisticated set of PWAs (Marler & Boudreau, 2017). Using DT, HR professionals may design a more sophisticated set of PWAs to forecast the impact of various HR interventions (Marler, & Boudreau, 2017; Sahay, 2014). They may also develop a more sophisticated set of TEPs using PWAs for predicting accurate outcomes of various training investments. Thus, this study proposed that PWAs will strengthen the relationship between HR professionals' DT and the set of TEPs they use for evaluating training outcomes.

2. Theoretical Framework

2.1 Design thinking

DT is an iterative approach for problem-solving that characterizes a creative and analytic process that allows individuals to experiment, design and prototype models, gather feedback, and then redesign again (Neck & Greene, 2011; Liedtka, 2017). The DT approach has become widespread across a variety of domains (Stovang & Nielsen, 2015; Black, Gardner, Pierce, & Steers, 2019), including business, innovation, and entrepreneurship (Koh et al. 2015) due to its potential of consistently challenging novel ideas and solutions (Linton & Klinton, 2019). The organizational scholars view DT as a synergic interaction between three critical areas of inspiration, ideation, and implementation rather than just a structured set of rules or milestones (Brown & Katz, 2019). It has the potential to strengthen problem-solving skills (Simons *et al.,* 2011) to identify creative alternatives based on sophisticated, emotionally satisfying, and meaningful experiences (Ben-Gal, 2019). DT contributes to organizational profitability as a collaborative approach to identify solutions for 'wicked' problems by exploring new opportunities (Hobday *et al.,* 2012).

2.2 Predictive workforce analytics

There is no consensus on a single overarching definition of PWAs (Huselid, 2018). The PWAs are the indicators based on artificial intelligence-based predictive models used for systematic reporting on various workforce aspects for making human resource management decisions (Bassi, 2011; Malisetty, Archana, & Kumari, 2017). PWAs are based on an evidence-based management approach that supports making better decisions from the business's people aspect. These quantifiable measurement tools range from simple HR metrics to highly sophisticated predictive modeling-based measures (Bassi, 2011, p. 16; Huselid, 2018). It also refers to 'quantitative and qualitative data and information management to obtain insights and support for decision-making about an organization's human resources (Ben-Gal, 2019; Sarivastava & Mohsin, 2020). Different terms are used interchangeably to the concept of PWAs, including 'HR analytics,' 'people analytics,' 'workforce analytics,' and 'human capital analytics' (Ben-Gal, 2019). This study relies on the usage of the term PWAs. Since workforce analytics help quantifies workforce contributions, they may enhance workflow and employee productivity (Hota & Gosh, 2013; Sarivastava & Mohsin, 2020). Gartner (2012) views workforce analytics as an advanced set of data analysis tools and metrics for comprehensive workforce performance measurement and improvement. PWAs involve workforce management metrics, which determine what needs to measure the workforce, and analytics, determining how essential metrics can be managed and improved for business success (Levenson & Harris, 2011).

2.3 Training evaluation practices

Training evaluation is a systematic human resource management process that HR professionals use to determine the value of training (Goldstein, 1989; Phillips, 2012; Phillips & Phillips, 2016) and its linkage with organizational objectives, organizational strategy, and organizational structure (Martinez & Stuart, 2011). HR professionals strategically use TEPs to justify training investments (Guerci et al., 2010; Brown, 2002). The literature is full of various training evaluation frameworks, including TKM (The Kirkpatrick Model, 2006), Return on Investment (ROI) model (Phillips, 2012), Performance Improvement framework by Swanson and

Holton (1999). The Kirkpatrick model is one of the most renowned models. Most training evaluation frameworks originated from TKM. This study relies on the 5-levels model of a training evaluation framework that involves four levels of TKM and the fifth level of Return on Investment (ROI) framework by Phillips (2012).

2.4 Hypothesis

2.4.1 Design Thinking and Training evaluation practices

The firm's RBV may also support the relationship between DT and TEPs. RBV explains that organizations utilize their resources to increase competitiveness (Boselie, Brewester, & Paauwe, 2009). The organizations invest a significant proportion of their financial resources in training their professionals to gain a competitive advantage. The training evaluation only may demonstrate how these dollars spent on training intervention contribute to the organizational performance (Steele, Mulhearn, Medeiros, Watts, Connelly, & Mumford, 2016). RBV also explains that organizations use sophisticated HR practices to govern their human resources' behavior to gain competitive advantage (Morris, Snell, & Lepak, 2006). Training evaluation is also a sophisticated set of practices that companies use to justify their financial resources' investment in training and development programs (Pineda, 2010; Grohmann & Kauffeld, 2013).

Like the previous hypothesis, this study also argues a positive relationship between DT and sophisticated TEPs inside an organization. As discussed previously, HR professionals with high-level DT competency may use more sophisticated statistical techniques to enhance workforce data's predictive power (Claus, 2019). Since HR professionals need to use TEPs to justify their financial investments in training activities (Pineda, 2010; Grohmann & Kauffeld, 2013), they prefer more sophisticated statistical techniques with the greater predictive power of training in front of top management. The HR professionals with a high level of DT would choose to organize, analyze, and present workforce training data more meaningfully because the management accepts the value of any activity in dollar terms only (Phillip, 2012). Hence, they may formulate testable questions related to the training evaluation because DT allows HR professionals to raise testable workforce-related research questions (Claus, 2019). Therefore, this study hypothesized:

Hypothesis 1: DT is positively related to firms' use of sophisticated TEPs such that the firms whose HR professionals have a higher level of DT use a more sophisticated set of TEPs.

2.4.2 Design Thinking and predictive workforce analytics

Human resource management has transformed due to rapid demographic changes occurring within the organization due to globalization and information technology development (Kapoor & Sherif, 2012; Sparrow, 2012; Fulmer & Ployhart, 2013). Significantly, the traditional HR metrics have turned unsuitable for various human resource management decisions in the current technological and environmental contexts (Fink, 2010; Handa, 2014). As a combination of empathy and engineering, DT emerges as an appropriate decision-making approach that offers a creative and practical problem-solving opportunity for innovative products and services to satisfy customer preferences (Levenson et al., 2011). Applying analytics-driven solutions using state-of-the-art statistical tools and techniques could be challenging. Yet, the management scientists agree that a priori integration of DT in analytics-driven business decisions offers an appropriate blend of business viability, technical feasibility, sensibility, and consumer needs (Harris et al., 2011). DT is an essential professional and managerial competency for increasing organizational profitability by resolving existing business problems through novel opportunities (Hobday et al., 2012). DT also appears as an essential competency for HR professionals to develop and apply the modern skillset required to succeed in today's highly technological and globally competitive world (Shute & Becker, 2010). HR professionals need DT competency to deal with strategic and operational HR problems through analytical skills (Angrave et al., 2016; Rasmussen & Ulrich, 2015) for manipulating information technology (Angrave et al., 2016; Douthitt & Mondore, 2014).

This study used RBV (Barney et al., 2001) to posit that the DT mindset of HR professionals facilitates the firms to implement PWAs for managing their workforce issues. According to the firm's RBV (Wernerfelt, 1984), the resources include semi-permanent assets of the firm, including human capital. Further, the cognitive factors are precious to differentiate among human capital quality (Castanias & Helfat, 2001). Borrowing this perspective, we view design thinking as one of the essential cognitive capacities. Similarly, considering the RBV of the firm, we also propose that the firms prefer hiring human resources with a higher level of DT for competitive advantage. Hence, this study investigated a positive association between a firm's human resource professionals' DT and the firm's tendency to use PWAs for workforce decisions.

This study advocates that a DT mindset allows HR professionals to manipulate PWAs to design improved solutions for HR issues. They will be more likely to use workforce-related data to make strategic HR decisions and address operational workforce requirements if they have a DT mindset. Since DT is an iterative approach that allows continuous experimenting (Neck & Greene 2011), HR professionals' DT mindset facilitates better use of PWAs. On the other hand, the organizations whose HR Professionals lack a DT mindset may lack experimenting PWAs. They are more likely to continue with those traditional HR metrics, which, unfortunately, have turned unsuitable for workforce decisions in the current technological and environmental context (Fink, 2010; Handa, 2014).

The RBV of the firm' explains how investing in human capital may harness firms' performance and competitiveness (Boselie & Paauwe, 2009). The application of RBV in human resource management suggests that the firms may acquire a competitive advantage with the help of human capital and human processes (Wright, Dunford, & Snell, 2001). Further, the firms use their human capital to develop more sophisticated HR processes (strategies, systems, and routines) that are unique and inimitable (Barney, Wright, & Ketchen 2001; Wright et al., 2001). Hence, human capital helps firms develop more sophisticated HR strategies, systems, and routines because only humans possess cognitive capabilities. This perspective of RBV explains that a higher level of DT competency may better position the firms to integrate state-of-the-art technological solutions in their existing human resource management set processes to make them more unique and inimitable. Integrating artificial intelligence in conventional human resource management processes in PWAs offers HR professionals with a DT mindset a better opportunity to differentiate their HR processes. Hence, this study hypothesized that the organizations with HR professionals with a DT mindset are more likely to apply PWAs than the companies whose HR professionals lack DT. DT competency may help HR professionals apply more sophisticated statistical techniques to enhance workforce data's predictive power (Claus, 2015). Consequently, they may organize, analyze, and present data in a more meaningful way. Similarly, they may formulate testable workforce-related research questions using a DT mindset (Claus, 2019). Hence, this study hypothesized that:

Hypothesis 2: DT is positively related to the use of PWAs **such that the firms whose HR professionals have a higher level of DT use more PWAs.**

2.4.3 PWAs and TEPs

This study has also hypothesized a positive relationship between PWAs and TEPs using the firm's RBV. The RBV of the firm explains that the firms develop strategic capabilities and core competencies to gain competitive advantage based on the degree to which they possess and manage their resources (Amit & Schoemaker, 1993; Barney, 1991; Barney et al., 2001; Sirmon et al., 2011). These strategic capabilities are not merely built on firms' physical or financial resources but the technological, reputational, and human capital (Größler & Grübner, 2006; Lado & Wilson, 1994). Hence, this study views PWAs as a strategic organizational capability built on technological resources. In this view, PWAs also offer an opportunity to improve organizational performance for gaining competitive advantage as a unique and value-producing technical resource (Marler & Boudreau, 2017).

This study's basic premise is that PWAs support human resource management professionals in creating a more sophisticated set of TEPs. PWAs is an ideal approach for designing TEPs because they use predictive analytics tools and techniques using internal data (e.g., headcounts, product mappings, financial statistics, and budgetary information) and external data (e.g., surveys, salary tables, syllabuses, and training program materials) for making a variety of workforce-related decisions (Levenson, 2011). PWAs use a holistic approach that goes beyond mere data collection and analysis; they can quantify the effects of various HR initiatives (Chadwick, Super, & Kwon, 2015). Hence, PWAs emerge as an ideal approach for human resource professionals to design more sophisticated techniques for quantifying the effects of TEPs. Therefore, the organizations using PWAs as a strategic capability will be more likely to use a more sophisticated set of TEPs to determine training value. PWAs provide appropriate information for measuring workforce efficiency to make more accurate decisions and improve organizational performance by identifying loopholes in the workforce management process

(Ringo, 2012). Despite spending millions of dollars on workforce training, organizations strive for modern approaches to determine their training investments' value because the traditional methods are becoming obsolete (Pineda, 2010). Training evaluation also involves a systematic collection of data to determine the value of training and make relevant decisions (Patton, 1997). Due to the integration of modern predictive techniques, training evaluation professionals may find PWAs an ideal opportunity for TEPs. They may also benefit from PWAs to improve their strategic capability in training evaluation.

Since the organizations invest billions of dollars in workforce training and implementing PWAs for making workforce decisions, the organizational managers may be favorably inclined to determine the return of such significant financial investments. Hence, the top corporate members would also prefer that PWAs competency be applied in the context of training evaluation so that more appropriate and predictive information may be obtained for future decisions related to the workforce training. Consequently, training evaluation professionals will likely use a more sophisticated set of TEPs based on PWAs. Hence, this study hypothesized that the organizations that benefit from PWAs are more likely to use more sophisticated TEPs.

Hypothesis 3: Firms' use of PWAs is positively associated with the firms' use of TEPs such that the firms which use PWAs more frequently use a more sophisticated set of TEPs.

2.4.4 The mediating role of PWAs between DT and TEPs

This study has also examined the mediating role of PWAs between DT and TEPs. We have already discussed that DT encourages organizational members to use unique HR matrices (Levenson et al., 2011) to identify the solutions for wicked problems for corporate-level decision-making (Marler & Boudreau, 2017). Since PWAs and TEPs are matrices sets, we hypothesized that organizational members with DT mindset adapt PWAs to design a more sophisticated set of TEPs further. The firm's RBV supports strengthening the role of PWAs between DT and TEPs. According to RBV, the organizations compete to acquire a larger pool of physical, financial, technological, and human resources to enhance their organizational capabilities and develop core competencies for gaining a competitive advantage over their rival firms (Lepak & Snell, 2003). Human resources improve the organizational capacity to utilize DT, while technological resources strengthen their ability to manipulate novel technical solutions to resolve contextual issues. The organizations poach more talented human resources from each other (Asadullah et al., 2015) and try to benefit from modern technological solutions. Such organizations are more likely to find innovative solutions for their routine practices. The organizations may choose to acquire professionals of DT mindset for employing data analytics to forecast the return of workforce investments. Such firms will develop a more sophisticated set of PWAs compared to the companies whose human resources lack DT. Subsequently, the organizations that adopt modern practices are more likely to create a more sophisticated set of procedures to determine their HR investments' outcomes.

Since firms invest a significant amount of money on training interventions, the organizational managers with DT may also manipulate their technological core competencies to employ data analytics in the training evaluation domain to determine the expected or the actual outcomes of training investments. Hence, organizations with a more incredible pool of professionals with a higher level of DT would be highly likely to employ workforce analytics. Consequently, they may exploit data analytics for designing a more sophisticated set of TEPs. Hence, this study hypothesized that:

H4: Firms' use of PWAs mediates the relationship between DT and firms' use of TEPs.

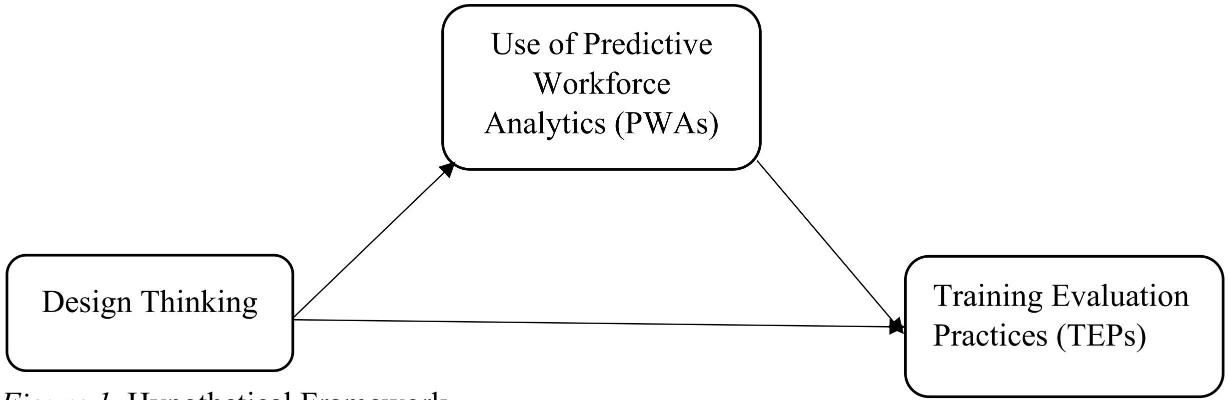

Figure 1. Hypothetical Framework

3. Method

3.1 Procedure

This quantitative study is based on cross-sectional data. The population consisted of human resource management professionals working in subsidiaries of multinational corporations (MNCs) operating in Pakistan. The targeted unit of analysis included HR professionals (like Trainers, HR analysts, and managers, both middle and senior level) involved in organizational decision making related to workforce management like using PWAs, conducting training, or designing a specific set of training evaluations. These HR trainers and analysts were knowledgeable about policies and practices for managing human resource decisions, including TEPs. This study used the purposive sampling method combined with the snowball sampling technique (Cooper & Schindler, 2006:402). We generated a list of subsidiary MNCs which were using PWAs. Then, we visited the potential respondents physically and requested them to participate in the survey. Initially, we distributed 300 questionnaires with a cover letter that ensured the anonymity of answers, including a brief explanation of the research. The fundamental objective of ensuring confidentiality using a cover letter was to mitigate the social desirability bias resulting from survey research (Roxas & Lindsay, 2012). One hundred eighty respondents returned the filled questionnaires. The response rate was 53.8%.

3.2 Measures

3.2.1 DT and PWAs: Scale development and validation

3.2.1.1 Development of initial pool of items and content validation

Table 1
Initial pool of items for PWAs implementation

Scale items	Never (1)	Rarely, in less than 10% of the chances (2)	Occasionally, in about 30% of the chances (3)	Sometimes, in about 50% of the chances (4)	Frequently, in about 70% of the chances (5)	Usually, in about 90% of the chances (6)	Every time (7)
1. Workforce Planning[a]	1	2	3	4	5	6	7
2. Talent Acquisition[a]	1	2	3	4	5	6	7
3. Talent Development[a]	1	2	3	4	5	6	7
4. Compensation & Benefits[a]	1	2	3	4	5	6	7
5. Productivity & Performance[a]	1	2	3	4	5	6	7
6. Culture & Diversity[a]	1	2	3	4	5	6	7
7. Employee Engagement[a]	1	2	3	4	5	6	7
8. Employee Retention[b]	1	2	3	4	5	6	7
9. Employer Branding[b]	1	2	3	4	5	6	7
10. Managing employee risks[b]	1	2	3	4	5	6	7
11. Forecasting employee outcomes[b]	1	2	3	4	5	6	7
12. Measuring Return on investment of HR Initiatives[b]	1	2	3	4	5	6	7
13. Solving specific critical business issues[b]	1	2	3	4	5	6	7
14. Meeting increased regulatory requirements[c]	1	2	3	4	5	6	7
15. Better management of costs and productivity in variable and uncertain business conditions[c]	1	2	3	4	5	6	7
16. Reducing turnover[c]	1	2	3	4	5	6	7
17. Developing a talent pipeline for succession planning[c]	1	2	3	4	5	6	7
18. Identifying the right hires of all positions[c]	1	2	3	4	5	6	7

a. HR Process Analytics; b. Strategic HR Analytics; c. HR Effectiveness Analytics

The literature suggests a couple of instruments measuring design thinking (Chesson, 2007; Greene, Gonzalez, & Papalambros, 2019) . Unfortunately, there are specific issues related to these scales. First, although the concept of design thinking originated from the engineering discipline, the available scales are also validated in the same context (Greene et al., 2019) by collecting data from engineering professionals as a unit of analysis. However, this study emphasized the validation of design thinking in the business context, and the unit of analysis also consisted of business professionals. Second, the scales' reliability, convergent validity, and discriminant validity were missing, particularly Greene et al. (2019) design thinking attitudes. Third, Chesson's design thinker profile offers a very complex construct structure. The design thinker profile consists of 3 sub-dimensions, including two first-order constructs (visual and optimism) and one second-order construct (collaborative discovery). The second-order sub-dimension 'Collaborative Discovery' consists of 4 different first-order sub-dimensions: engage, human, generate, and navigate. Hence, Chesson's design thinker profile presents a very complex and lengthy construct structure.

Similarly, we found a scale of big data and predictive analytics developed by Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba, & Roubaud (2019): three different dimensions: technical skills, managerial skills, and data-driven decision-making culture. However, this scale emphasizes big data analytics in general and lacks relevance to the workforce settings. Thus, we identified the need to develop and validate the scales of design thinking and workforce analytics with a more simplified structure. We developed the scales for both constructs and validated them by following the scale development method presented by Churchill (1979) and Hinkin (1998). Dosi et al. (2018) generated a pool of 84-items for measuring DT with items belonging to 19 different characteristics of the DT mindset. We developed a pool of 19-items measuring DT mindset based on these characteristics.

Similarly, we generated a pool of 30-items for measuring PWAs and followed the principles of item development described by MacKenzie and Podsakoff (2012). Following the approach suggested by existing literature (Khan, Moss, Quratulain, & Hameed, 2018; Armenakis, Bernerth, Pitts, & Walker, 2007; Tepper, Mitchell, Haggard, Kwan, & Park, 2015), we conducted a panel discussion with 8 HRM executive who attended formal training at a public sector Universities in Pakistan. This panel discussion was moderated by an HR Expert having 8-years post-PhD academic experience, while the panel participants have a minimum of 6-years' experience in the discipline of Human Resource Management. We requested the participants to examine the initial pool of the items from multiple perspectives. Then, we asked them to categorize the items of each variable into smaller groups. We also requested them to judge the relevance of the initial pool of items with their respective theme. They also recognized the most appropriate response format for scale anchors. We also asked panel discussion participants to ensure if the scale items are simple, direct, easy to understand by the target population, and avoid double-barreled and leading statements (Hinkins, 1998). The essential purpose was to establish the scales' content validity (Kimberlin & Winterstein, 2008). We also obtained help from a Ph.D. qualified faculty member of a public sector University for English language editing of the generated items. The panel discussion resulted in an 18-item scale for PWAs (Table 1) and a 21-item scale of DT (Table 2). The experts also agreed to a 7-point Likert type rating scale (ranging from 1 (never) to 7 (every time) for the construct of PWAs, while a 4-point Likert type rating scale (ranging from irrelevant (1) to very relevant (4) for design thinking.

Table 2
Initial pool of items for DT

Scale items	Irrelevant	Somewhat relevant	Relevant	Very relevant
1. Tolerance for being comfortable with uncertainty[a]	1	2	3	4
2. Embracing Risk[a]	1	2	3	4
3. Human centeredness[a]	1	2	3	4
4. Empathy for people[a]	1	2	3	4
5. Mindfulness and awareness of the process[b]	1	2	3	4
6. A holistic view (detailed information about the system to consider the problem from a broader perspective)[b]	1	2	3	4
7. Problem reframing[b]	1	2	3	4
8. Team Working[c]	1	2	3	4
9. Collaborate and work with teams of diverse discipline[c]	1	2	3	4
10. Open to different perspectives[c]	1	2	3	4
11. Learning oriented[c]	1	2	3	4
12. Experimentation or learn from a mistake or failure[c]	1	2	3	4
13. Critical thinking, ability to think differently and to challenge common beliefs[d]	1	2	3	4
14. Curiosity[d]	1	2	3	4
15. Abductive thinking (ability to find a logical solution based on observation[d]	1	2	3	4
16. Envision (ability to predict or foresee future desired goals	1	2	3	4
17. Creative confidence (ability to solve complex issues)	1	2	3	4
18. Learning-oriented (appetite for learning)[c]	1	2	3	4
19. Optimism (positive thinking)[a]	1	2	3	4
20. Ability to learn from mistakes[c]	1	2	3	4
21. Desire to make something different[d]	1	2	3	4

a. People and risk-orientation; b. System Thinking; c. Collaborative Learning; d. Critical Thinking.

3.2.1.2 Exploratory factor Analysis

We collected data from 80 HRM professionals serving in 29 different multinational organizations to identify the internal structure of measures used for design thinking and predictive workforce analytics. We performed exploratory factor analysis (EFA) on the 18-items scale of predictive workforce analytics and the 21-items scale of Design Thinking using SPSS. We used two statistical measures (i.e., Kaiser Mayer Olkin (KMO) criteria (Kaiser, 1974) and

Bartlett's Test of Sphericity (Bartlett, 1954)) to determine if our sample size is appropriate for performing an EFA (Pallant, 2020; p. 191). A KMO value of 0.6 or greater with a significant Bartlett's test of Sphericity (p <.05) demonstrates that the dataset is appropriate for factor analysis (Pallant, 2020). First, we performed EFA on the 19-items of predictive workforce analytics using Principal axis factoring and Promax rotation as an extraction method. The values of KMO (KMO = 0.874) exceeded the minimum threshold, and Bartlett's Test of Sphericity was also significant (1044.482, p < .001). Hence, the assumption of the minimum sample size required for performing EFA was satisfied. Initially, we set the data free to disclose as many factors as possible. The initial EFA revealed a 5-factors solution with an unclear pattern and cross-loadings. We performed alternate tests by restricting the factors to 4, 3, 2, and 1. Among these tests, a 3-factor solution (75.01% variance) was most suitable after removing 4-items (PWA6, PW8, PW9, & PW14) due to cross-loading on more than one factor. The first factor consisted of 6 items (PWA1, PWA2, PWA3, PWA4, PWA5, & PWA7). We named this factor "HR Process Analytics." The second factor consisted of 4 items (PWA10, PWA11, PWA12, PWA13). We called this factor "Strategic HR Analytics." The third factor also consisted of 4 factors (PWA15, PWA16, PWA17, PWA18). We named this factor "HR effectiveness Analytics." Overall, EFA results supported 3-factors solutions contrary to the five themes identified in the panel study.

Next, we performed EFA on the 21-items of DT. The results of Kaiser Mayer Olkin criteria (KMO = 0.702) and Bartlett's Test of Sphericity (547.131, p <.001) demonstrated the suitability of data to perform EFA (Bartlett, 1954; Kaiser, 1974). Initially, we set the data free to disclose as many factors as possible. The initial EFA model revealed a 5-factors solution with an

Table 3
Results of exploratory factor analysis (EFA) items of PWAs and factor loadings

Scale items	Factor1: HR Process	Factor2: HR Effectiveness	Factor3: HR Strategy
1. Workforce Planning (PWA1)	0.927		
2. Talent Acquisition (PWA2)	0.822		
3. Talent Development (PWA3)	0.786		
4. Compensation & Benefits (PWA4)	0.705		
5. Productivity & Performance (PWA5)	0.632		
6. Employee Engagement (PWA6)	0.539		
7. Managing employee risks (PWA10)		0.855	
8. Forecasting employee outcomes (PWA11)		0.783	
9. Measuring Return on investment of HR Initiatives (PWA12)		0.649	
10. Solving specific critical business issues (PWA13)		0.606	
11. Better management of costs and productivity in variable and uncertain business conditions (PWA15)			0.878
12. Reducing turnover (PWA16)			0.836
13. Developing a talent pipeline for succession planning (PWA17)			0.772
14. Identifying the right hires of all positions (PWA18)			0.690

unclear pattern and cross-loadings. We performed alternate tests by restricting the factors to 4, 3, 2, and 1. A 4-factor solution (54.5% variance) was most suitable after removing 2-items (DT12 & DT 19) due to cross-loading on more than one factor. The first factor consisted of 4-items (DT1, DT2, DT3 & DT4). We named this factor "People-orientation." The second factor consisted of 5-items (DT5, DT6, DT7, DT17, & DT18). We named this factor "Critical Thinking." Third factor consisted of 4-items (DT8, DT9, DT10, & DT11). We named this factor "Collaborative Learning." The fourth factor also consisted of 4-items (DT13, DT14, DT15, & DT16). We labeled this factor "System thinking." Overall, EFA results supported 3-factors solutions contrary to the five themes identified in the panel study.

Table 4

Results of Exploratory Factor Analysis (EFA) Items of PWAs and Factor Loadings

Scale items	Factor1: People-Orientation	Factor 2: Teamwork	Factor 3: Critical Thinking	Factor 4: System Thinking
1. Empathy for people (DT4)	0.67			
2. Human centeredness (DT3)	0.70			
3. Embracing Risk (DT2)	0.75			
4. Tolerance for Being comfortable with Uncertainty (DT1)	0.76			
5. Team Working (DT8)		0.80		
6. Collaborate and work with teams of diverse discipline (DT9)		0.73		
7. Open to different perspectives (DT10)		0.73		
8. Critical thinking, ability to think differently and to challenge common beliefs (DT13)			0.91	
9. Curiosity (DT14)			0.74	
10. Experimentation or learn from a mistake or failure (DT12)			0.80	
11. Abductive thinking (ability to find a logical solution based on observation (DT15)			0.49	
12. Learning-oriented (appetite for learning) (DT18)				0.80
13. Creative confidence (ability to solve complex issues) (DT17)				0.75
14. Optimism (positive thinking) (DT19)				0.70
15. Problem reframing (DT7)				0.52

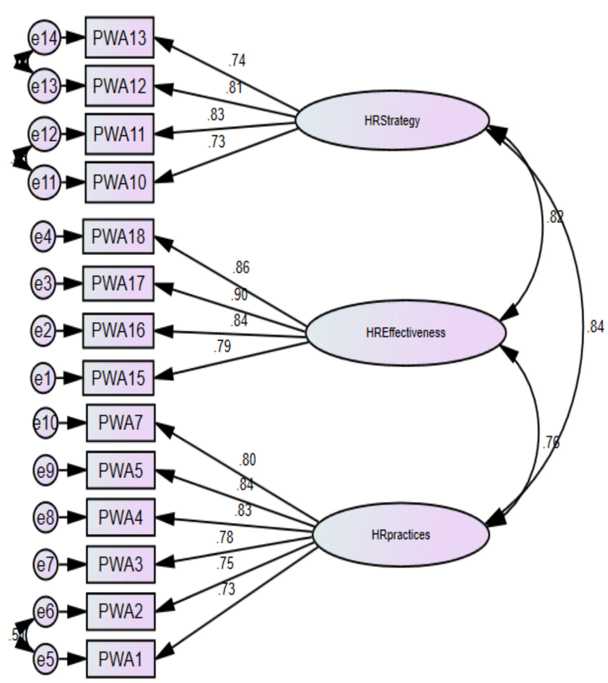

Figure 2. Finalized Confirmatory Factor Model of PWAs

We collected data from a second sample that consisted of 80 different HR Professionals serving in the subsidiaries of the same Multinational Corporations (MNCs). We performed confirmatory factor analysis using a structural equation modeling software, i.e., AMOS 24th version. First, we performed CFA to confirm the structure of PWAs. The initial CFA model with three dimensions of PWAs demonstrated a good fit (Table 5). We retained items with the factor loadings above 0.40 (Costello & Osborne, 2005; DeVellis, 2003) if the convergent and discriminant validity of the constructs was not compromised. We draw covariance between the error terms of those items (Figure 2 and Figure 3) whose modification indices exceeded 20 to improve the model fit. We also tested an alternative CFA model by introducing the construct as unidimensional. However, we found that the three-factor solution fitted more adequately. We repeated the same procedure with the construct of DT to validate its underlying structure as explored during EFA. The CFA results demonstrated that the 4-dimensional model of DT was better than a unidimensional CFA model (Table 5).

Table 5

Estimates for Model Fit Indices against different Confirmatory Factor Models

Variables		Chi-square	Degrees of Freedom	CMin/DF	CFI	TLI	RMR	RMSEA
Predictive Workforce Analytics	3-dimensional Model	118.19	71	1.66	0.94	0.92	0.08	0.09
	2-Dimensional Model	150.36	73	2.06	0.89	0.87	0.10	0.12
Design Thinking	4-dimensional Model	85.81	55	1.56	0.90	0.90	0.04	0.08
	Unidimensional Model	172.73	61	2.82	0.63	0.65	0.56	0.15

Table 6
Convergent and Discriminant validity of dimensions of predictive work analytics

	CR	AVE	MSV	MaxR(H)	HRS	HRP	HRE
Strategic HR Analytics(HRS)	0.91	0.64	0.62	0.91	**0.80**		
HR Process Analytics (HRP)	0.91	0.72	0.61	0.92	0.76	**0.857**	
HR Effectiveness Analytics(HRE)	0.89	0.676	0.62	0.89	0.79	0.78	**0.82**

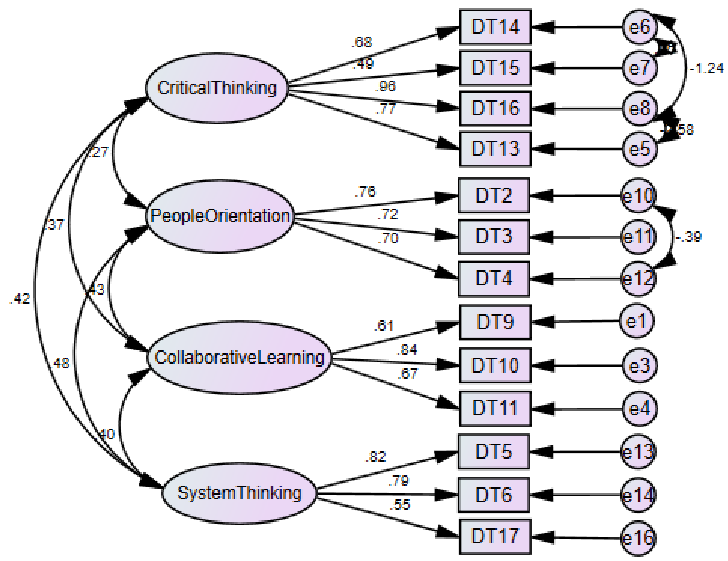

Figure 3. Finalized Confirmatory Factor Model of DT (PWAs)

Table 7
Convergent and discriminant validity of dimensions of DT

Variables	CR	AVE	MSV	MaxR(H)	ST	CTPS	PRO	CL
System Thinking (ST)	0.77	0.53	0.23	0.77	0.73			
Critical Thinking (CT)	0.75	0.51	0.18	0.79	0.43	0.71		
People-orientation (PRO)	0.83	0.56	0.17	0.94	0.27	0.37	0.75	
Collaborative Learning (CL)	0.77	0.546	0.23	0.818	0.48	0.40	0.42	0.73

3.3 Dependent Variable: Training Evaluation Practices

Twitchell et al. (2000) used a scale to measure Training Evaluation practices of manufacturing sector firms in the USA. This scale is based on "The Kirkpatrick Framework (TKM)" and "Return on Investment (ROI)," comprising five different sub-dimensions including reaction (3-items), learning (9-items), on-the-job behavior (13-items), results (11-items), and ROI (9-items). Asadullah et al. (2015) used this scale to measure training evaluation practices in the call center industry. We requested respondents to estimate the percentage of the various methods listed below (column 2) that their organization uses to evaluate the training programs against each level/sub-dimension. The respondents provided their ratings on a 6-point rating scale ranging from 1(0%) to 6(100%).

Table 8
Discriminant and Convergent Validity of Training Evaluation Practices (TEPs)

	CR	AVE	MSV	MaxR(H)	Results	Reac	Learn	Behav	ROI
Results	0.77	0.53	0.19	0.77	**0.73**				
Reaction	0.77	0.53	0.19	0.81	0.43	**0.73**			
Learning	0.74	0.50	0.12	0.91	0.31	0.26	**0.71**		
Behavior	0.77	0.53	0.12	0.77	0.29	0.22	0.34	**0.72**	
ROI	0.75	0.51	0.18	0.77	0.43	0.37	0.29	0.34	**0.71**

4. Findings

4.1 Descriptive Statistics

The descriptive statistics of the variables are given in Table 9. Table 9 demonstrates that multicollinearity is not an issue as the strength of correlations among the critical variables of the study is not high. We followed the approach of Kock (2015) and Kock and Lynn (2012) to examine the common method bias in the data. This approach allows the researcher to explore

VIF values (VIF ≤ 3.3) to find the existence of common method bias in the dataset. We regressed standardized residuals of the criterion variable on all the variables. Since VIF values (1.15, 1.79, and 1.77) were far below the given range (3.3), we concluded that common method bias was not a severe issue in our data.

Table 9

Means, Standard Deviations, and Correlations among the Variables

Variables	Mean	Standard Deviation	**1**	**2**	**3**	**4**	**5**	**6**
1. Gender	---	---						
2. Age	36	4.63	-.229					
3. Experience	8.79	2.33	-.254	.723**				
4. Education	15.83	1.46	.132	-.058	.112			
5. Design Thinking	3.09	0.33	.108	.065	.107	-.044		
6. Predictive Workforce Analytics	4.93	0.8	-.027	.010	-.033	-.019	.338**	
7. Training Evaluation Practices	4.35	0.54	-.114	-.048	-.216	-.051	.318**	.651**

**. Correlation is significant at the 0.01 level (2-tailed).

4.2 Hypothesis Testing

Since our study participants were nested within 27 different MNS subsidiaries, we decided to test our hypotheses using multilevel mediation analysis. We tested hypotheses using an SPSS computational named MLMED (https://njrockwood.com/mlmed). Rockwood developed this process macro to simplify the multilevel analyses for mediation and moderated-mediation models. Mainly, we tested a 1-1-1 multilevel mediation model because our theoretical framework incorporated level 1 variables only. The results are presented in Table 8. The statistical results demonstrated an insignificant direct relationship between DT and TEPs at both within (level-1: $\beta = 0.190$; $p = 0.102$) and between subjects (level-2: $\beta = 0.074$; $p = 0.757$). Hence, hypothesis H1 was not supported. The statistical results demonstrated a significant

Table 10

Indirect Effect of DT on TEPs through PWAs (1-1-1 Multilevel Mediation Model)

Hypothesized Relationships	Within-Subject Effects (Level-1) Beta-Coefficients (Standard Error) T-Values	Between Subject Effects (Level-2) Beta-Coefficients (Standard Error) T-Values	Results
Direct Effect(H1): Design Thinking→Training Evaluation Practices	0.191(0.12)1.657	0.07(0.24)0.31	Not Supported
H2: Design Thinking→Predictive Workforce Analytics (Path a)	0.70(0.19)3.69***	1.55(0.54)2.88***	Supported
H3: Predictive Workforce Analytics → Training Evaluation Practices (Path b)	0.32(0.05)5.99***	0.58(0.07)7.86***	Supported
Indirect Effect (H4): Design Thinking→Predictive Workforce Analytics →Training Evaluation Practices	0.22(0.07)3.11**	0.91(0.347)2.68**	Supported

***. Relationship is significant at the 0.001 level (2-tailed).**. Relationship is significant at the 0.01 level (2-tailed). *. Relationship is significant at the 0.01 level (2-tailed).

relationship between DT and PWAs within (level-1: β = 0.70; p = 0.004) and between subjects (level-2: β = 1.552; p = 0.000). Hence, hypothesis H2 was supported. Further, the statistical results demonstrated a significant relationship between predictive workforce analytics and TEPs at both within (level-1: β = 0.317; p = 0.004) and between subjects (level-2: β = 0.583; p = 0.000). Hence, hypothesis H3 was also supported. Finally, the statistical results demonstrated a significant indirect effect of DT on TEPs through PWAs at both within (level-1: β = 0.222; p = 0.002) and between subjects (level-2: β = 0.905; p = 0.007). Hence, hypothesis H4 was also supported.

5. Discussion and Theoretical Implications

There is a lack of empirical studies on how DT may contribute to TEPs via PWAs in the TEPs literature. Our study contributes to the body of knowledge on TEPs by presenting several theoretical implications. By conceptualizing HR professionals' DT mindset as a critical human capital attribute, this study investigated its impact on the firms' use of PWAs and TEPs. Although DT does not directly influence TEPs, the findings demonstrated that it indirectly affects TEPs through firms' PWAs. This study also revealed a positive relationship between DT and PWAs. Finally, the results also showed a significant relationship between the firm's PWAs and TEPs. Based on these findings, this study contributes to the extant literature on DT and HRM practices (TEP and PWAs) and offers several implications.

First, we hypothesized and tested the positive relationship between DT and its use of PWAs. The existing literature on HR management practices largely overlooked the need to examine the role of HR professionals' DT in different firm-level HRM practices. We build on the firm's RBV to understand how HR professionals' DT mindset leads firms to use PWAs. Our finding adds to the extant literature on RBV by demonstrating that HR can be a source of competitive advantage. One reason could be that humans can employ their cognitive processes to help the firms' design unique and inimitable HR management processes (Barney, Wright, & Ketchen 2001; Wright et al., 2001; Batt, 2002).

Second, this study found that the firm's use of PWAs positively relates to the firm's use of a more sophisticated set of TEP. This finding also complies with the firms' RBV. We explicate that firms may acquire a competitive advantage with the help of human processes, which serve as a resource for the firms to improve their capabilities (Wright, Dunford, & Snell, 2001; Sarivastava & Mohsin, 2020). Based on the findings, this study helps us understand how the firms may use PWAs to design a more sophisticated TEP set. Moreover, it highlights the firms' need for complementarity between different sets of HR practices. Past literature on HRM practices ignored the practice-to-practice relationships. Therefore, this finding adds to HRM literature that focused on the complementarity between HR practices (e.g., Shipton et al., 2006; Beugelsdijk, 2008; Foss et al., 2015) for organizational value addition.

Finally, this study found that DT significantly and indirectly relates to TEP through the mediating role of a firms' PWAs. This finding explains how HR professionals' DT mindset may help the firms improve the use of a more sophisticated set of TEP through their implementation of PWAs. This finding follows the notion of RBV and has direct implications for the literature on the intersection of DT, PWAs, and TEP (Barney, Wright, & Ketchen 2001; Wright et al., 2001). Hence, hiring HR professionals with a DT mindset may help the firms use innovative HR practices (i.e., PWAs) that may further enhance the firms' use of a more sophisticated set of TEP. Our findings add to the HRM literature that stresses the need for complementarity between HR practices. We explain that the cognitive capability of HR can enable the firm to acquire an appropriate level of complementary between different sets of HR practices.

6. Human Resource Development Implications

This study also offers implications for human resource development (HRD) practitioners. Gravan et al. (2019) criticized that many learning and development functions cannot effectively utilize data for predictive decision-making related to organizational learning and development activities. Hence, they suggested that HRD professionals for a specific change in their mindset to develop their predictive analytics skills. Our findings identified DT as a mindset that HRD professionals may need for developing PWAs skills related to organizational learning and development. This study also considers the DT mindset an essential cognitive resource for developing workforce management practices. As a unique cognitive resource of HR professionals, DT can facilitate firms to modernize their existing workforce management practices. Training HR professionals on DT may benefit firms to use modern workforce management tools (such as workforce analytics and artificial intelligence) effectively. Thus, they may design a more sophisticated set of TEPs and forecast the most beneficial training investment initiatives.

The managers may also use screening mechanisms to identify the HR professionals with an appropriate level of DT. For this purpose, managers can use the DT measure introduced in the current study (Table 2) to identify and develop HR professionals' level of DT mindset. This approach may support organizational development as DT may enable HR professionals to adapt workforce analytics and evaluation practices for predictive decisions related to organizational learning and development activities. The significant indirect relationship between DT and TEP through PWAs demonstrates that DT may foster more sophisticated training evaluation practices conditional to their essential role in PWAs. This finding implies that the interventions designed to enhance managerial DT may be tied to the development PWAs skills of HR Professionals for developing a more sophisticated set of TEPs to predict effective training and development programs.

7. Limitations and future research

This study bears various limitations that offer the opportunity for future research in the same line of inquiry. First, this study is based on the data collected from HR professionals of subsidiaries of Multinational Firms operating in Pakistan. The key reason to collect data from such subsidiary firms was that these firms might be using predictive analytics. They may also consider other local and public firms using predictive analytics. Second, future studies may emphasize measuring the DT of Top Management Team members of such firms. Third, the hypothetical model tested in the current study was limited to TEP. Future research may extend this area of inquiry by considering a variety of other HRM practices. Fourth, future research may expand the mediation model tested in the current study to various employee-level outcomes (e.g., transfer of knowledge) and firm-specific outcomes (e.g., knowledge management and organizational forgetting, productivity, and financial performance). Finally, the researchers may use qualitative research to explore how DT leads HR professionals to think about workforce analytics and other HRM practices to determine different organizational outcomes.

8. Conclusion

Training evaluation is one of the most ignored areas of investigation despite significant firm-level investment in workforce training. Unfortunately, existing research has largely ignored the mechanisms which explain why some firms may use a more sophisticated set of TEPs. This study used RBV to explain how HR professionals' DT helps MNCs using PWAs to implement a more sophisticated set of TEPs. This empirical investigation found that HR professionals' DT mindset does not directly predict firms' use of sophisticated TEPs. However, DT significantly contributes to the firms' TEPs through the exploitation of PWAs. Since TEPs are a sub-set of HR Practices, it's sense-making that without improving workforce decision-making capacity based on PWAs, DT may not directly improve firms' TEPs.

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