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Cultural Intelligence, HR Practices and Job Performance: The Mediating Role of Technological Adaptation Among Healthcare Professionals in the UAE

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Abstract **– Purpose – The healthcare sector in United Arab Emirates (UAE) puts together one of the world's most culturally diverse clinical workforces with very quick digital transformation. This study explores and learns how cultural intelligence (CQ) and human resource (HR) practices moulds healthcare professional's technological adaptation (TA) and, with the help of it, their job performance (JP). Design/methodology/approach – Among 400 nurses, doctors and allied health professionals who work in Dubai and Abu Dhabi, a cross-sectional survey was conducted, they were selected through proportionate and stratified sampling. HR practices (18 items), job performance (12 items), technological adaptation grounded in UTAUT (16 items), and Validated scales for CQ (20 items) were used. Data were analysed using regression and partial least squares structural equation modelling (PLS-SEM) with 5,000 bootstrap resamples. This was followed by mediation and multi-group analysis. Findings – CQ (β = 0.345) and HR practices (β = 0.259) predicted technological adaptation, which was the strongest predictor of job performance (β = 0.457). Technological adaptation mediated the effects of both CQ (indirect effect = 0.158) and HR practices (indirect effect = 0.118) on performance. Wholly, the model explained 24.0% of the variance in TA and 36.8% in JP, and the structural relationships were invariant across the two Emirates. Originality/value – The study merges cultural intelligence theory, the ability–motivation–opportunity (AMO) view of HRM and the Unified Theory of Acceptance and Use of Technology (UTAUT) in a single model, positioning technological adaptation as the mechanism through which individual cultural capabilities and organisational HR systems translate into clinical performance in a multicultural setting.**

Keywords **– Cultural intelligence; HR practices; technological adaptation; UTAUT; job performance; healthcare professionals; UAE; PLS-SEM**

I. Introduction

Globally, the healthcare systems are being totally reshaped by artificial intelligence (AI)-assisted diagnostics, clinical decision support, and electronic medical records (EMR), telehealth. However, the value of these technologies depends less and less on their acquisition than on if the professionals who use them adapt their work routines to exploit them (Holden & Karsh, 2010; Greenhalgh et al., 2017). Poor and improper adaptation could result in documentation burden, lost productivity and workarounds, whereas effective adaptation could enhance the speed, safety and quality of care.

The UAE provides a distinct context for learning this problem. Their health authorities, the Dubai Health Authority (DHA) and the Department of Health – Abu Dhabi (DoH), have hugely invested in digital health infrastructure, which includes emirate-wide health information exchanges. Simultaneously, the clinical workforce is expatriate: in the present sample only 5.5% of respondents were Emirati, with the majority of them originating from the Indian subcontinent, the Philippines and other Arab countries. Technology adoption in such settings is a social process in which communication, peer learning and shared norms are filtered through cultural differences. Therefore clinicians adapt to novel technologies while working within teams, and treating patients, from many different cultural backgrounds.

Two sets of antecedents are highly relevant in this environment. At the individual level, cultural intelligence, a person's capability to function effectively in culturally diverse settings (Earley & Ang, 2003), might facilitate professionals to learn from diverse colleagues, interpret social cues around new systems and cope with the stress of change. At the organisational level, HR practices like training and development, performance management and cross-cultural team management might build the ability, motivation and opportunity needed to adopt technology (Appelbaum et al., 2000; Jiang et al., 2012). And even though each stream is well developed, research has very rarely examined them together or tested whether technological adaptation is the mechanism linking them to job performance, specifically in Gulf healthcare settings.

This study acknowledges that space by answering three questions: (1) Do CQ and HR practices affect healthcare professionals' technological adaptation? (2) Does technological adaptation impact their job performance? (3) Does technological adaptation mediate the relationships between CQ, HR practices and job performance? The study contributes to theory by integrating CQ theory, the AMO framework and UTAUT, and to practice by presenting evidence to inform HR policy and technology rollout strategies in multicultural hospitals.

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II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Theoretical foundation

The AMO framework proposes that HR practices improve outcomes by enhancing employees' ability, motivation and opportunity to perform (Appelbaum et al., 2000; Boxall & Macky, 2009; Jiang et al., 2012). The model delineates on three complementary perspectives. Cultural intelligence theory conceptualises CQ as a multidimensional capability comprising metacognitive, cognitive, motivational and behavioural facets (Ang & Van Dyne, 2008; Ang et al., 2007). UTAUT describes technology acceptance through performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003, 2012). Altogether, these perspectives suggest that individual capabilities and organisational systems mould how professionals take up and use technology, and that adaptation is a proximal driver of performance.

Cultural intelligence and technological adaptation

In multicultural hospitals, learning a new clinical system is a very rare and solitary activity. Professionals depend on colleagues, super-users and trainers from different cultures to understand the workflow. Also they must communicate system-mediated information to patients with diverse expectations. Metacognitive CQ lets individuals to view and adjust assumptions during these exchanges, cognitive CQ supplies knowledge of cultural norms, motivational CQ sustains effort under the stress of adjustment, and behavioural CQ lets appropriate verbal and non-verbal communication (Ang et al., 2007). The CQ has been linked to adaptation and efficiency across cultural boundaries (Ott & Michailova, 2018; Rockstuhl et al., 2011). In terms of UTAUT, culturally intelligent professionals benefit more from social influence and peer support, and to perceive technology as more useful and easier to use because they could draw on a diverse network for help. Hence:

H1: Cultural intelligence has a positive effect on healthcare professionals' technological adaptation.

HR practices and technological adaptation

HR practices could be understood as the organisational infrastructure for adaptation. Training and development construct the skills that are required to use EMR, telehealth and AI tools (ability), they are performance management that recognises and rewards effective use signals that adaptation is valued (motivation); and cross-cultural team management fosters information sharing and constructive conflict resolution within diverse teams (opportunity). All these mechanisms correspond closely to UTAUT's facilitating conditions and social influence (Venkatesh et al., 2003). Research on high-performance work systems shows that bundles of these practices mould employee attitudes and discretionary behaviour (Jiang et al., 2012).

Hence:

H2: HR practices have a positive effect on healthcare professionals' technological adaptation.

Technological adaptation and job performance

Job performance is multidimensional, has adaptive performance, contextual performance and task performance (Borman & Motowidlo, 1993; Pulakos et al., 2000; Koopmans et al., 2011). Professionals who have adapted to clinical technologies can complete documentation and retrieve information more efficiently (task performance), support colleagues in using systems (contextual performance) and respond more effectively to changing clinical demands (adaptive performance). Human factors research in healthcare similarly puts forth argument, that technology produces benefits only when it is integrated into clinical work (Holden & Karsh, 2010).

Hence:

H3: Technological adaptation has a positive effect on healthcare professionals' job performance.

The mediating role of technological adaptation

If CQ and HR practices bolden technological adaptation, and adaptation improves performance, then adaptation should transmit part of their effect on performance. Direct effects are also plausible, because CQ improves interpersonal effectiveness and HR practices influence performance through channels unrelated to technology. Therefore, partial mediation is expected. Figure 1 presents the conceptual model.

H4a: Technological adaptation mediates the relationship between cultural intelligence and job performance.

H4b: Technological adaptation mediates the relationship between HR practices and job performance.

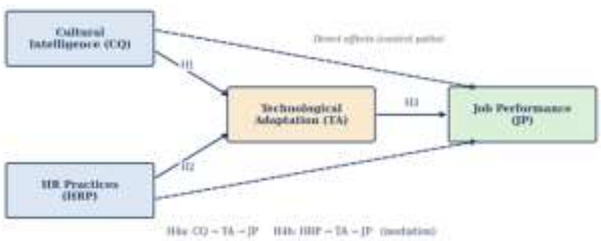

Figure 1. Conceptual model

III. METHODOLOGY

Research design, population and sample

A quantitative, and cross-sectional survey design was acquired. The population contained licensed healthcare professionals practising in Dubai and Abu Dhabi. A proportionate stratified sampling design was applied on two dimensions: Emirate (50% Dubai, 50% Abu Dhabi) and profession (50% nurses, 30% doctors, 20% allied health professionals), reflecting on the composition of the clinical workforce. The sample at the end had 400 respondents (Dubai n = 200; Abu Dhabi n = 200; nurses n = 200; doctors n = 120; allied health n = 80). The sample size of 400 surpasses the minimum of 384 recommended by Krejcie and Morgan (1970) for large populations. A prior power analysis in G∗Power (Faul et al., 2007) for a regression with

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three predictors (medium effect size $f^2 = 0.15$, $\alpha = 0.05$, power = 0.95) showed a minimum of 119 respondents. So the sample provides statistical power for the structural model, and the questionnaire was self-administered and needed approximately 15–18 minutes to complete. Participation was completely voluntary and anonymous. Also informed consent was taken before participation, and no personally identifying information was collected. The data were handled in line with the UAE Personal Data Protection Law (Federal Decree-Law No. 45 of 2021) and APA ethical guidelines.

Measures

All constructs were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), which was adapted from established instruments. Cultural intelligence was measured with the 20-item Cultural Intelligence Scale (Ang & Van Dyne, 2008) covering metacognitive (4 items), cognitive (6), motivational (5) and behavioural (5) CQ. HR practices (18 items) covered training and development, performance management and cross-cultural team management (6 items each), adapted from Jiang et al. (2012) and Boxall and Macky (2009). Technological adaptation (16 items) was operationalised with the help of the four UTAUT dimensions (performance expectancy, effort expectancy, social influence and facilitating conditions; 4 items each), adapted from Venkatesh et al. (2003, 2012) and Holden and Karsh (2010), and referenced to technologies like EMR, telehealth, clinical decision support and AI-assisted diagnostics. Job performance (12 items) covered task, contextual and adaptive performance (4 items each). All four constructs were modelled as second-order constructs.

Data analysis

First the descriptive statistics, correlations, independent-samples t-tests and one-way ANOVA were computed. Then the measurement model was evaluated for indicator reliability, internal consistency (Cronbach's α, composite reliability), convergent validity (AVE) and discriminant validity (Fornell–Larcker criterion and HTMT), following Hair et al. (2022), Fornell and Larcker (1981) and Henseler et al. (2015). A multi-group analysis compared Dubai and Abu Dhabi. The structural model was estimated in SmartPLS 4 (Ringle et al., 2022) using bias-corrected bootstrapping with 5,000 resamples. Indirect effects were tested following Preacher and Hayes (2008) and classified using Zhao et al. (2010). Common method bias was addressed through procedural remedies (anonymity, separated sections and neutral item wording) and assessed through collinearity diagnostics (Podsakoff et al., 2003).

IV. RESULTS

Respondent profile

Table 1 collectively summarises the respondent profile. The workforce was predominantly expatriate, with respondents from India (34.0%), the Philippines (24.8%) and other Arab countries (17.0%) forming the largest groups. Most respondents were female (61.5%), aged 25–44 years (72.7%) and held a bachelor's degree or higher (87.8%). Major part of them worked in private hospitals (56.2%), and 65.0% used clinical technologies daily. This confirms that technology is an integral part of respondents' work.

Table 1. Respondent profile (N = 400)

Variable	Category	n	%	Variable	Category	n	%
Emirate	Dubai	200	50.0	Nationality	Indian	136	34.0
	Abu Dhabi	200	50.0		Filipino	99	24.8
Profession	Nurse	200	50.0		Arab (non-UAE)	68	17.0
	Doctor	120	30.0		Pakistani	42	10.5
	Allied health	80	20.0		Emirati	22	5.5
Gender	Female	246	61.5		European / Other	33	8.3
	Male	154	38.5	Hospital type	Private	225	56.2
Age	Below 25	30	7.5		Public	175	43.8
	25–34	153	38.2	UAE tenure	< 2 years	52	13.0
	35–44	138	34.5		2–5 years	157	39.2
	45 and above	79	19.8		6–10 years	127	31.8
Education	Diploma	49	12.2		> 10 years	64	16.0
	Bachelor's	208	52.0	Technology use	Daily	260	65.0
	Master's	112	28.0		Several times/week	89	22.2
	Doctorate	31	7.8		Weekly or less	51	12.7

Measurement model

All 66 items showed enough dispersion (variances > 0.80) and approximate normality (|skewness| and |kurtosis| < 2). The measurement model was evaluated at two levels. At the first-order level (Table 2), average outer loadings ranged from 0.769 to 0.838. This exceeds the 0.708 threshold. Cronbach's α ranged from 0.799 to 0.890 and composite reliability from 0.869 to 0.916. This is above the 0.70 benchmark, and confirms internal consistency. AVE values ranged from 0.592 to 0.702, above 0.50, confirming convergent validity (Hair et al., 2022).

Table 2. First-order measurement model: reliability and convergent validity

Construct	Dimension	Items	Mean	Avg. loading	Cronbach's α	CR (ρc)	AVE
Cultural Intelligence	Metacognitive CQ	4	3.669	0.790	0.799	0.869	0.624
	Cognitive CQ	6	3.642	0.803	0.890	0.916	0.645
	Motivational CQ	5	3.661	0.822	0.880	0.912	0.675
	Behavioural CQ	5	3.654	0.788	0.847	0.891	0.621
HR Practices	Training & development	6	3.655	0.769	0.862	0.897	0.592
	Performance management	6	3.651	0.785	0.875	0.906	0.616
	Cross-cultural team mgmt.	6	3.632	0.802	0.889	0.915	0.643
Technological Adaptation	Performance expectancy	4	3.556	0.838	0.858	0.904	0.702
	Effort expectancy	4	3.589	0.836	0.857	0.903	0.700
	Social influence	4	3.618	0.831	0.850	0.899	0.690
	Facilitating conditions	4	3.614	0.816	0.833	0.889	0.666
Job Performance	Task performance	4	3.618	0.826	0.844	0.895	0.681
	Contextual performance	4	3.618	0.799	0.811	0.876	0.639
	Adaptive performance	4	3.631	0.831	0.850	0.899	0.690

Note. CR = composite reliability; AVE = average variance extracted. Thresholds: loading ≥ 0.708; α and CR ≥ 0.70; AVE ≥ 0.50.

At the second-order level, the four higher-order constructs also met the criteria: CQ (α = 0.817, CR = 0.879, AVE = 0.645), HR practices (α = 0.792, CR = 0.878, AVE = 0.707), technological adaptation (α = 0.830, CR = 0.887, AVE = 0.663) and job performance (α = 0.801, CR = 0.883, AVE = 0.716). Discriminant validity was established with the help of two criteria. Under the Fornell–Larcker criterion, the square root of each construct's AVE (diagonal of Table 3) exceeded its correlations with all other constructs. All HTMT ratios (above the diagonal) were less than the conservative 0.85 threshold, the highest being 0.700 for technological adaptation and job performance (Henseler et al., 2015). All full collinearity VIF values were less than 1.35, which is well below the 3.3 cut-off, and indicated that common method bias is not a serious concern.

Correlations and group comparisons

Table 3 showed that all constructs were positively and significantly correlated ($p < .001$). The strongest link was between technological adaptation and job performance ($r = .572$). No correlation approached .90, which indicated no multicollinearity concern. At the dimension level, within-construct correlations (e.g., training and cross-cultural team management, $r = .63$) exceeded between-construct correlations, providing preliminary evidence of discriminant validity. Among the UTAUT dimensions, social impact showed the highest correlations with task ($r = .43$) and adaptive performance ($r = .47$).

Table 3. Construct correlations, Fornell–Larcker criterion and HTMT ratios

Construct	CQ	HRP	TA	JP
CQ	0.803	0.377	0.511	0.503
HRP	0.303	0.841	0.446	0.404
TA	0.423	0.363	0.814	0.700
JP	0.405	0.325	0.572	0.846

Note. Bold diagonal values are the square root of AVE; values below the diagonal are Pearson correlations (all $p < .001$); values above the diagonal are HTMT ratios.

Independent-samples t-tests showed no significant differences in any construct between Dubai and Abu Dhabi (all $p > .21$), men and women (all $p > .53$), or public and private hospitals (all $p > .23$). All effect sizes were negligible ($|d| \leq 0.12$). Likewise one-way ANOVA showed no significant differences across nurses, doctors and allied health professionals (all $p > .18$). All these results showed

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that perceptions were homogeneous across subgroups and support pooling the data for structural analysis.

Structural model and hypothesis testing

Variance inflation factors were less than 1.35 for all predictors. Altogether, CQ and HR practices explained 24.0% of the variance in technological adaptation (R^2 = 0.240). The full model explained 36.8% of the difference in job performance (R^2 = 0.368). Technological adaptation made a medium-to-large contribution to explaining performance (f^2 = 0.252; Cohen, 1988). This removed it and reduced R^2 for job performance from 0.368 to 0.209. Table 4 reports the bootstrap results.

Table 4. Structural model results (5,000 bootstrap resamples)

Hypothesis / path	β	Boot SE	t	95% CI	Decision
H1: CQ → TA	0.345	0.052	6.621	[0.242, 0.445]	Supported
H2: HRP → TA	0.259	0.045	5.683	[0.168, 0.347]	Supported
H3: TA → JP	0.457	0.045	10.183	[0.368, 0.543]	Supported
CQ → JP (direct)	0.181	0.044	4.101	[0.092, 0.267]	Significant
HRP → JP (direct)	0.104	0.044	2.387	[0.018, 0.189]	Significant

CQ had a positive effect on technological adaptation (β = 0.345, t = 6.621), supporting H1. HR practices also had a significant positive effect (β = 0.259, t = 5.683), supporting H2. Even though CQ was the stronger antecedent. Technological adaptation had the largest effect in the model, on job performance (β = 0.457, t = 10.183), supporting H3. The direct effects of CQ (β = 0.181) and HR practices (β = 0.104) on performance also remained significant.

Mediation analysis

Table 5 shows the indirect effects. Both were significant, with bootstrap confidence intervals excluding zero. And because the direct effects had the same sign, both relationships represent complementary partial mediation (Zhao et al., 2010). Technological adaptation accounted for almost 47% of the total effect of CQ and 53% of the total effect of HR practices on performance. H4a and H4b were therefore supported.

Table 5. Mediation results

Path	Indirect effect	Boot SE	t	95% CI	Total effect	VAF	Type
H4a: CQ → TA → JP	0.158	0.028	5.588	[0.105, 0.216]	0.339	46.6%	Complementary partial
H4b: HRP → TA → JP	0.118	0.024	4.988	[0.073, 0.166]	0.222	53.2%	Complementary partial

Multi-group analysis

A parametric multi-group test compared the TA → JP path between Emirates. The coefficient was almost identical in Dubai (β = 0.457) and Abu Dhabi (β = 0.452), and the difference was not significant (z = 0.048, p = 0.962). This indicates that the relationship between technological adaptation and performance holds across both regulatory environments.

V. DISCUSSION

This study examined how cultural intelligence and HR practices impact the healthcare professionals' technological adaptation and job performance in the UAE's multicultural healthcare environment. All hypotheses were supported, and yielded three main insights.

First, cultural intelligence came up as a stronger predictor of technological adaptation than HR practices. In a workforce where most clinicians are expatriates, adapting to technology depends substantially on the capability to learn from and communicate with culturally different colleagues and patients. It is also consistent with the relatively strong correlations between social influence and other constructs, indicating that adaptation in these hospitals is a socially embedded process. The finding extends CQ research, which has focused on expatriate adjustment and cross-cultural effectiveness (Ott & Michailova, 2018), into the domain of technology adoption.

Second, HR practices improved technological adaptation, supporting the AMO logic that training, performance management and cross-cultural team management create the ability, motivation and opportunity to use new systems (Appelbaum et al., 2000; Jiang et al., 2012). The smaller direct effect of HR practices on performance, when compared with their indirect effect. It also suggested that a substantial part of the value of HR investment in digitalising hospitals works through technology-related capability rather than independently of it.

Third, technological adaptation was the dominant predictor of job performance and a significant mediator. The partial mediation shows that CQ and HR practices also improve performance through other channels, such as teamwork and communication. This supports the view that the benefits of clinical technology are realised through the people who integrate it into their work (Holden & Karsh, 2010;

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Greenhalgh et al., 2017). Conclusively, the absence of notable differences across Emirates, professions, genders and hospital sectors suggests that the model is robust across the main segments of the UAE clinical workforce.

Theoretical implications

The study makes three main theoretical contributions. It integrates CQ theory, the AMO framework and UTAUT into one model, demonstrating that individual cultural capability and organisational HR systems are complementary antecedents of technology adaptation. It positions technological adaptation as an explanatory mechanism linking these antecedents to multidimensional job performance, responding to calls to move from adoption intentions to adaptation in actual clinical work. It also extends UTAUT-based research to a highly multicultural, Gulf healthcare context, where cultural diversity is a defining feature rather than a peripheral variable.

Practical implications

For hospital managers and HR departments, the findings suggest that technology rollouts should be designed as cultural and technical change programmes. Recruitment and on boarding could incorporate CQ assessment and development, while digital training will be delivered in culturally diverse cohorts and include cross-cultural communication content. Team leaders should be equipped to manage diverse teams and to use culturally respected peers as technology champions. Performance management systems can easily explicitly recognise effective technology use and peer support. For regulators such as the DHA and DoH, the results suggest that workforce policies, including continuing professional development requirements, could integrate digital competence and cultural competence rather than treating them separately.

Limitations and future research

Various limitations should be noted. The cross-sectional design limits causal inference, and longitudinal studies could track adaptation during specific system implementations. All variables were self-reported, raising the possibility of common method bias and inflated performance ratings. Further future studies could use supervisor ratings or objective indicators like documentation time or error rates. The sample was limited to Dubai and Abu Dhabi, so replication in the Northern Emirates and other Gulf countries is needed. The model explained a moderate share of variance in technological adaptation. This indicates that other factors, like digital literacy, age, leadership style and system usability, deserve attention. Any research in the future can also test moderators such as experience and tenure in the UAE, analyse the model at the dimension level, and apply importance-performance map analysis or configurational methods such as fsQCA.

VI. CONCLUSION

As the UAE hospitals continue to digitalise, performance increasingly relies on how well a culturally diverse workforce adapts to technology. This study shows that cultural intelligence and HR practices both strengthen technological adaptation, and that adaptation is the strongest route to improved job performance among nurses, doctors and allied health professionals. Organisations that invest simultaneously in their people's cultural capabilities and in supportive HR systems are likely to gain more from their technology investments. Therefore integrating cultural, human and technological considerations is necessary for building a high-performing healthcare workforce.

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