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Integrating IoT, Deep Learning, HRM, and Financial Analytics for Environmental Sustainability, Employee Well-Being, and Organizational Performance

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ABSTRACT: Organisations are increasingly investing in Internet of Things (IoT) infrastructure, deep learning analytics, digitally enabled human resource management (HRM) and financial analytics, yet empirical evidence on how these capabilities jointly translate into environmental, human and economic outcomes remains fragmented, particularly in emerging economies. Drawing on the resource-based view, the natural-resource-based view and the job demands–resources model, this study ,we examine how IoT adoption, deep learning analytics capability, sustainable and digital HRM practices and financial analytics capability shape environmental sustainability performance and employee well-being, how these two outcomes in turn affect organizational performance, whether they act as mediators, and whether the pattern differs between manufacturing and service firms. A structured questionnaire was answered by 360 managers working in 64 medium and large firms across Andhra Pradesh and Telangana, India. The data were analysed with exploratory and confirmatory factor analysis, covariance-based structural equation modeling (maximum likelihood), bias-corrected bootstrapping with 2,000 resamples and multi-group analysis. Environmental sustainability performance rose with IoT adoption ($\beta = 0.32$, $p < 0.001$), deep learning analytics ($\beta = 0.24$, $p < 0.001$) and financial analytics ($\beta = 0.15$, $p < 0.05$), but not with HRM practices ($\beta = 0.06$, $p > 0.05$). Employee well-being, on the other hand, depended on HRM practices ($\beta = 0.41$, $p < 0.001$) and was unrelated to deep learning analytics. Well-being ($\beta = 0.41$) and environmental sustainability ($\beta = 0.21$) both lifted organizational performance, with the model accounting for 44% of its variance. The effect of IoT on performance passed

entirely through environmental sustainability, the effects of deep learning and financial analytics passed partly through it, and the effect of HRM passed entirely through well-being. The HRM–well-being relationship was considerably stronger in service firms. Technology and people capabilities, in short, add value along separate paths, and managers need to plan them together rather than one at a time.

1. INTRODUCTION

Firms are now judged on more than profit. Regulators, investors and employees also ask how much they pollute and how well they treat their people. Elkington (1997) called this the triple bottom line, and the 2030 Agenda for Sustainable Development (United Nations, 2015) has since turned it into a policy expectation. Over the same period, a new generation of digital tools has reached the shop floor and the back office. Connected sensors under the banner of the Internet of Things (IoT) now report on machines, meters and buildings continuously (Atzori et al., 2010; Gubbi et al., 2013). Deep learning models can find patterns and anomalies in those data that older statistical methods would miss (LeCun et al., 2015). HR departments have begun to rely on analytics and digital platforms (Marler & Boudreau, 2017; Tambe et al., 2019), and finance teams use dashboards and predictive models to track costs and returns as they happen (Chen et al., 2012; Davenport & Harris, 2007).

Each of these capabilities has its own literature, but the literatures rarely meet. Work on Industry 4.0 and big data has connected digital technologies with operational and sustainability results (Kamble et al., 2018; Dubey et al., 2019; Ghobakhloo, 2020; Bag et al., 2020). A separate body of HRM research ties people-management practices to well-being and firm performance (Huselid, 1995; Van De Voorde et al., 2012; Guest, 2017). Financial analytics, for its part, is seldom treated as a capability in its own right in sustainability studies. We therefore know little about how technology, people practices and financial intelligence combine, which outcome each one actually moves, and by what route each eventually reaches the bottom line.

The Indian setting makes the question a practical one. Programmes such as Make in India and Digital India have pushed the country to become a hub for both manufacturing and digital services, and India has committed to lowering the emissions intensity of its economy. Andhra Pradesh and Telangana contain a large share of the firms involved: pharmaceutical, automobile, steel, engineering and food processing units, together with IT/ITES, banking and logistics companies, clustered around Visakhapatnam, Sri City, Hyderabad and Vijayawada–Guntur. These firms face regulators who want lower emissions and less waste, export customers who want evidence of sustainability, and a young, mobile workforce that cares about work–life balance. Yet digital investment across them is patchy, and managers have little hard evidence about which capabilities bring environmental, human and financial returns.

There is also an open debate about what advanced analytics does to the people who work with it. Intelligent systems can take over routine tasks and lighten the load. They can just as easily speed up work, increase monitoring and leave employees feeling less in control, a pattern described as technostress (Tarafdar et al., 2007). No study we are aware of has tested, in one structural model, whether deep learning capability helps or harms employee well-being, or whether people-oriented HRM practices contribute anything to environmental results. Nor has anyone checked whether these links look different in manufacturing firms, where the environmental footprint is physical and direct, and in service firms, where employees are the main productive resource.

Against this background, the study sets out to (i) estimate how IoT adoption, deep learning analytics capability, sustainable and digital HRM practices and financial analytics capability affect environmental sustainability performance; (ii) estimate how HRM practices and deep learning analytics capability affect employee well-being; (iii) assess how environmental sustainability performance and employee well-being affect organizational performance; (iv) test whether environmental sustainability performance and employee well-being mediate these effects; and (v) compare the structural relationships in manufacturing and service firms. In doing so, it offers an integrated model of technological, human and financial capabilities, tested with covariance-based SEM, bootstrapped mediation and multi-group analysis, on data from firms in one of India's fastest-growing industrial regions.

2. REVIEW OF LITERATURE

2.1. Theoretical foundation

Three theoretical lenses inform the model. The first is the resource-based view (RBV), according to which firms outperform rivals when they hold resources and capabilities that are valuable, rare and difficult to copy (Barney, 1991). Studies of IT capability have carried this argument into the digital domain, showing that what matters is the capability to use technology, not the amount spent on it (Bharadwaj, 2000; Melville et al., 2004). Teece et al. (1997) add that resources produce value when firms can combine and reconfigure them as conditions change, and big data analytics capability has been described in exactly these terms (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019). The second lens is the natural-resource-based view (NRBV), which treats the ability to prevent pollution and manage products responsibly as a source of advantage in itself (Hart, 1995). This fits the older claim that environmental improvement and competitiveness need not be in conflict (Porter & van der Linde, 1995; Russo & Fouts, 1997). The third lens is the job demands–resources (JD-R) model. It holds that resources such as autonomy, support, development and recognition improve well-being, while heavy demands produce strain (Bakker & Demerouti, 2007). Read together, the three theories lead us to expect technological and financial capabilities to work mainly on environmental outcomes, HRM to work mainly on employees, and both kinds of outcome to feed into organizational performance.

2.2. Digital, human and financial capabilities

IoT adoption. By IoT we mean networks of sensors, meters and connected devices that record and transmit data on physical assets and processes (Atzori et al., 2010; Gubbi et al., 2013). Inside a firm, adoption shows up as real-time tracking of energy, water, emissions and waste, as sensor feeds linked into enterprise systems, and as automatic alerts that prompt someone to fix a problem. Because resource flows become visible in fine detail, managers can spot waste and leakage that would otherwise stay hidden (Bibri, 2018; Ghobakhloo, 2020). Reviews of Industry 4.0 repeatedly list IoT among the main enablers of energy savings and waste reduction (Kamble et al., 2018).

Deep learning analytics capability. Deep learning methods are machine learning models built from many layers of neural networks; they learn useful features directly from large and complex data (LeCun et al., 2015). We define deep learning analytics capability as the degree to which a firm uses such models for prediction, anomaly detection and optimisation, and has the skills and infrastructure to run them. Research on big data and predictive analytics suggests that more advanced analytics leads to better decisions, better operations and better sustainability results (Gupta & George, 2016; Wamba et al., 2017; Dubey et al., 2019; Bag et al., 2020). Predictive maintenance, demand forecasting and energy optimisation are common examples of how deep learning can cut resource use and waste.

Sustainable and digital HRM practices. HRM practices influence what employees can do, how motivated they are and what opportunities they have to contribute (Huselid, 1995). Present-day HRM tends to mix a sustainability orientation, with its emphasis on flexible work, fair rewards and development (Guest, 2017), with digital tools such as HR analytics that keep track of workload and engagement (Marler & Boudreau, 2017; Tambe et al., 2019). Writers on green HRM go a step further and argue that training, appraisal and reward systems can carry environmental goals as well (Renwick et al., 2013; Jabbour & de Sousa Jabbour, 2016; Ren et al., 2018). Here we measure HRM practices through work–life support, training for digital skills, fair appraisal, and the use of HR analytics to watch workload and health.

Financial analytics capability. This capability covers the use of dashboards, predictive financial models and cost–benefit analytics, along with the joining up of financial and operational data for decisions (Chen et al., 2012; Davenport & Harris, 2007). With it, a firm can put numbers on the returns from energy-efficiency and clean-technology projects, choose the projects that pay best both financially and environmentally, and see what its resource use costs as it happens. Green investments that a conventional capital-budgeting exercise might reject can therefore get a fair hearing, and better control of costs and cash may improve financial results directly.

2.3. Environmental sustainability, employee well-being and organizational performance

Environmental sustainability performance, as used here, refers to measurable progress on energy intensity, emissions, waste and regulatory compliance. The NRBV argues that firms which cut pollution at its source pay less for inputs and compliance, earn a better reputation and reach customers who care about the environment (Hart, 1995; Russo & Fouts, 1997). Evidence

from manufacturing supply chains supports the claim that environmental practices improve economic and operational results (Zhu & Sarkis, 2004).

Employee well-being covers job satisfaction, a workload that people can cope with, balance between work and private life, and physical and mental health. Research going back to the "happy-productive worker" idea links well-being with better job performance (Wright & Cropanzano, 2000), and reviews of the HRM–performance link single out well-being as one of the main channels through which HRM reaches organizational results (Van De Voorde et al., 2012; Guest, 2017). We take organizational performance in a broad sense, covering profitability, productivity, operational efficiency and customer outcomes.

2.4. Research gap and hypotheses development

Four gaps stand out from this review. Digital technologies, HRM and financial analytics have mostly been examined in separate streams, so their relative and combined effects are unknown. Few studies separate an environmental path from a human path to performance inside one structural model. The possibility that advanced analytics changes employee well-being, for better or through technostress, has hardly been tested at the organisational level. And evidence from Indian manufacturing and service firms, let alone comparisons between the two, is thin. The hypotheses below follow from this discussion.

IoT and deep learning give managers a detailed picture of how resources move and predictive insight into how to use them better, and this should mean less energy, fewer emissions and less waste per unit of output (Kamble et al., 2018; Dubey et al., 2019; Ghobakhloo, 2020). Green HRM research suggests that HRM practices encourage environmentally responsible behaviour among employees (Renwick et al., 2013; Ren et al., 2018). Financial analytics, meanwhile, lets firms evaluate and rank sustainability investments. We therefore propose:

H1. *IoT adoption has a significant positive effect on environmental sustainability performance.*

H2. *Deep learning analytics capability has a significant positive effect on environmental sustainability performance.*

H3. *Sustainable and digital HRM practices have a significant positive effect on environmental sustainability performance.*

H4. *Financial analytics capability has a significant positive effect on environmental sustainability performance.*

The JD-R model treats flexibility, development, fair recognition and attention to workload as job resources, and such resources should improve well-being (Bakker & Demerouti, 2007; Guest, 2017). Deep learning capability could reduce workload by taking over routine analysis and improving planning, though it could also add monitoring and technostress (Tarafdar et al., 2007). Following the resource argument, we expect:

H5. *Sustainable and digital HRM practices have a significant positive effect on employee well-being.*

H6. *Deep learning analytics capability has a significant positive effect on employee well-being.*

In line with the NRBV and the happy-productive worker thesis (Hart, 1995; Wright & Cropanzano, 2000; Van De Voorde et al., 2012), we further expect:

H7. *Environmental sustainability performance has a significant positive effect on organizational performance.*

H8. *Employee well-being has a significant positive effect on organizational performance.*

Since environmental sustainability performance and employee well-being are treated as the outcomes through which capabilities create economic value, they should also act as mediators (Melville et al., 2004; Van De Voorde et al., 2012):

H9a–H9d. *Environmental sustainability performance mediates the relationships between (a) IoT adoption, (b) deep learning analytics capability, (c) HRM practices and (d) financial analytics capability and organizational performance.*

H10a–H10b. *Employee well-being mediates the relationships between (a) HRM practices and (b) deep learning analytics capability and organizational performance.*

Manufacturing firms leave a larger physical footprint on the environment, while service firms rely more on their people. The link between technology and the environment, and the link between HRM and well-being, may therefore be stronger in one sector than the other:

H11. *The structural relationships in the model differ significantly between manufacturing and service firms.*

The theoretical framework of the study is presented in Figure 1.

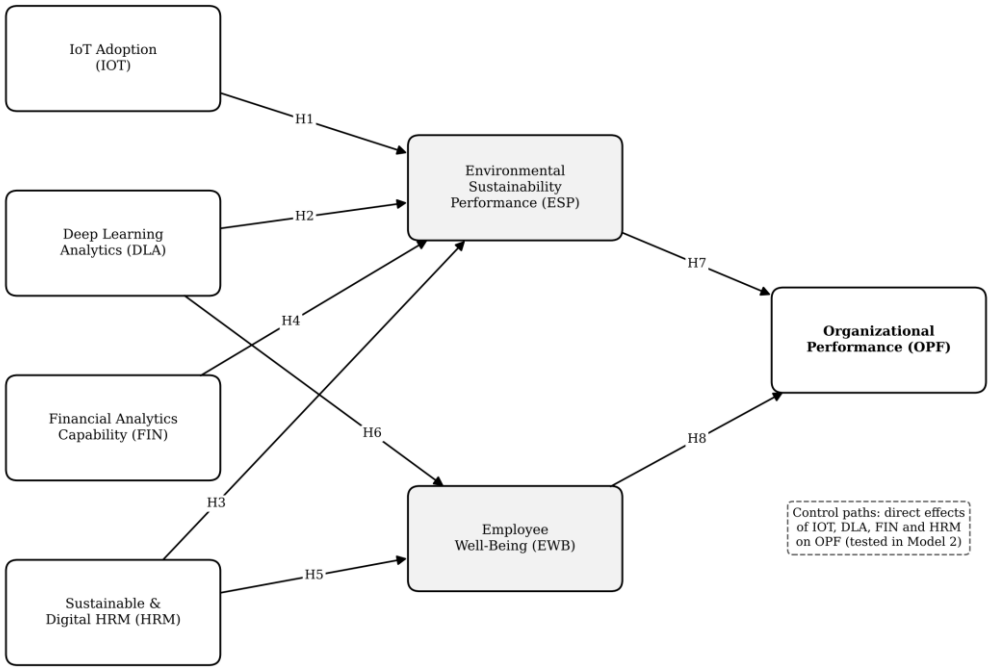


Figure 1. Theoretical model of the study.

3. RESEARCH METHODS

3.1. Study area description

Fieldwork took place in Andhra Pradesh and Telangana in southern India, in four industrial and technology clusters. Hyderabad, the capital of Telangana, is a major centre for IT/ITES, pharmaceuticals and financial services. Visakhapatnam is a port city with steel, pharmaceutical, engineering and logistics industries. Sri City–Tirupati is a multi-product special economic zone with automobile component, food processing and engineering units. Vijayawada–Guntur is a growing commercial and agro-processing region. Between them, the clusters cover both resource-heavy manufacturing and knowledge-based services, and so reflect the mix of environmental, human and financial pressures that firms in the region face.

3.2. Research design and approach

The design is cross-sectional, and both descriptive and explanatory. It describes how far firms have developed digital, human and financial capabilities, and it explains how these capabilities relate to organisational outcomes. The hypotheses come from established theory and earlier empirical work, and all data were gathered at a single point in time. A quantitative approach suited the aim of estimating direct, indirect and group-specific relationships in the proposed model.

3.3. Sampling method and sample size

The firm was the unit of analysis, and managers who knew about operations, HR, finance, IT or sustainability served as respondents. Since no complete list of firms using digital technologies existed, we used purposive-cum-stratified sampling. Medium and large firms (at least 250 employees) registered with state industrial development corporations and industry associations were divided by sector into manufacturing and services, and were contacted through their HR or corporate offices. In each firm that agreed to take part, four to eight managers from different functions were asked to respond, so that every capability was rated from more than one functional viewpoint. Sixty-four firms took part, 36 in manufacturing and 28 in services.

On sample size, Hair et al. (2019) advise a minimum of five respondents per item and ideally ten, which for a 28-item instrument means 140 to 280 respondents. Kline (2016) regards 200 or more cases as adequate for an SEM model of moderate complexity, and Wolf et al. (2013) report stable estimates at this size when loadings exceed 0.70 and each factor has at least three indicators. Because a multi-group comparison was also planned, we aimed for roughly 150 respondents per group. Of 480 questionnaires distributed, 402 came back. Removing incomplete and straight-lined returns left 360 usable responses (196 from manufacturing and 164 from services), an effective response rate of 75.0 percent.

3.4. Research instrument development

The questionnaire had two parts. Part A asked about the respondent and the firm. Part B contained 28 items, four for each of seven latent constructs, answered on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). IoT adoption items were adapted from Industry 4.0 studies (Kamble et al., 2018; Ghobakhloo, 2020). Items for deep learning analytics capability were drawn from big data analytics capability scales (Gupta & George, 2016; Wamba et al., 2017) and reworded for deep learning applications. HRM items came from Huselid (1995), Guest (2017) and Marler and Boudreau (2017); financial analytics items were developed from Chen et al. (2012) and Davenport and Harris (2007); environmental sustainability performance items were adapted from Zhu and Sarkis (2004); employee well-being items from Wright and Cropanzano (2000) and Guest (2017); and organizational performance items from Wamba et al. (2017) and Zhu and Sarkis (2004). Performance items asked about the respondent's organisation over the previous three years.

Three academics with expertise in information systems, HRM and finance, along with two senior practitioners, reviewed the items for content validity. A pilot with 40 managers led to small changes in wording. The final questionnaire was in English, which is the working language of managers in these firms, and was available on paper and online. Data collection ran from February to June 2026.

4. METHODS OF DATA ANALYSIS

Returned questionnaires were checked for completeness, coded and entered in IBM SPSS Statistics 26, and the dataset was screened for missing values, outliers and entry errors. Descriptive statistics summarise the respondents and the item scores. To uncover the underlying structure, we ran an exploratory factor analysis (principal component extraction, Varimax rotation). Following the two-step approach of Anderson and Gerbing (1988), the measurement model was then tested with confirmatory factor analysis in IBM SPSS AMOS 24. Reliability was judged from Cronbach's alpha and composite reliability (CR). Validity was judged from average variance extracted (AVE), maximum shared variance (MSV), the Fornell and Larcker (1981) criterion and the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015). The structural model was estimated by maximum likelihood, and indirect effects were tested with bias-corrected bootstrapping on 2,000 resamples (Preacher & Hayes, 2008), with mediation types classified as in Zhao et al. (2010). Differences between manufacturing and service firms were examined in a multi-group analysis that compared path coefficients through critical ratios (Byrne, 2016). Model fit was judged on absolute, incremental and parsimony indices (Hu & Bentler, 1999; Byrne, 2016).

5. FINDINGS

5.1. Profile of respondents and firms

Table 1 describes the 360 respondents. Men made up 248 (68.9%) of the sample and women 112 (31.1%). The most common age band was 36–45 years (139; 38.6%), followed by 25–35 years (104; 28.9%), and most respondents held a postgraduate degree (214; 59.4%). They worked in operations or production (92; 25.6%), IT and analytics (79; 21.9%), finance and accounts (71; 19.7%), human resources (68; 18.9%) and sustainability or EHS (50; 13.9%), so each capability was rated by managers who deal with it directly. Just over half were middle managers (189; 52.5%), and about a third had between 5 and 10 years of experience (121; 33.6%). Manufacturing firms supplied 196 respondents (54.4%) and service firms 164 (45.6%). Pharmaceuticals (58; 16.1%) and steel and engineering (52; 14.4%) were the largest manufacturing industries, and IT/ITES (71; 19.7%) the largest service industry. The typical firm employed between 1,000 and 4,999 people (148; 41.1%), and Hyderabad was the largest cluster (132; 36.7%).

Table 1. Profile of respondents and firms (N = 360).

Variable	Category	Frequency	Percent (%)
Gender	Male	248	68.9
	Female	112	31.1
Age (years)	25–35	104	28.9
	36–45	139	38.6
	46–55	86	23.9
	Above 55	31	8.6
Education	Graduate (B.Tech/B.Com/BBA)	97	26.9
	Postgraduate (MBA/M.Tech/MCA)	214	59.4
	Professional (CA/CMA) / Doctorate	49	13.6
Functional area	Operations / Production	92	25.6
	Human resources	68	18.9
	Finance and accounts	71	19.7
	IT / Analytics	79	21.9
	Sustainability / EHS	50	13.9
Managerial level	Junior / First-line	84	23.3
	Middle	189	52.5
	Senior	87	24.2
Work experience (years)	Less than 5	58	16.1
	5–10	121	33.6
	11–15	97	26.9
	More than 15	84	23.3
Sector	Manufacturing	196	54.4
	Services	164	45.6
Industry	Pharmaceuticals	58	16.1
	Automobile and components	44	12.2

Variable	Category	Frequency	Percent (%)
	Steel and engineering	52	14.4
	Food processing	42	11.7
	IT / ITES	71	19.7
	Banking and financial services	49	13.6
	Logistics	44	12.2
Firm size (employees)	250–999	133	36.9
	1,000–4,999	148	41.1
	5,000 and above	79	21.9
Location (cluster)	Hyderabad	132	36.7
	Visakhapatnam	104	28.9
	Sri City–Tirupati	68	18.9
	Vijayawada–Guntur	56	15.6

Note: EHS = environment, health and safety; ITES = IT-enabled services.

5.2. Descriptive statistics

Table 2 reports item means, standard deviations, skewness and kurtosis together with the EFA loadings. HRM practices received the highest ratings of any construct (M = 3.78, SD = 0.83), and the statement that HR policies support flexible work and work–life balance drew the strongest agreement (M = 3.93, SD = 0.91). Organizational performance came next (M = 3.77, SD = 0.84), then employee well-being (M = 3.68, SD = 0.85) and financial analytics capability (M = 3.66, SD = 0.87). IoT adoption sat in the middle (M = 3.63, SD = 0.83). Energy monitoring was its most common use (M = 3.82), while acting on IoT alerts was the least common (M = 3.44). Environmental sustainability performance was also rated moderately (M = 3.62, SD = 0.85), with waste reduction and recycling at the bottom of that scale (M = 3.48). Deep learning analytics capability had the lowest mean of the seven constructs (M = 3.49, SD = 0.86), and having the skills and infrastructure to build and run deep learning models was the lowest-rated item in the whole questionnaire (M = 3.41). People-oriented HRM, in other words, is fairly well established in these firms, but advanced analytics is still at an early stage.

Table 2. Factor loadings, descriptive statistics and normality measures.

Construct and items	FL	M	SD	S	K
IoT Adoption (IOT)					
IOT1 – Our organisation uses IoT sensors to monitor energy consumption in real time	.791	3.82	1.00	−0.61	−0.09
IOT2 – Smart meters and sensors track water use, emissions and waste generation at our facilities	.800	3.71	0.95	−0.21	−0.71

Construct and items	FL	M	SD	S	K
IOT3 – IoT devices are integrated with our operational systems (ERP/MES) for automatic data capture	.814	3.53	1.00	−0.20	−0.48
IOT4 – IoT-generated alerts are used to take corrective action on equipment and resource use	.804	3.44	0.99	−0.13	−0.60
Deep Learning Analytics Capability (DLA)					
DLA1 – Our organisation uses deep learning models (e.g., neural networks) to analyse large operational datasets	.798	3.61	1.01	−0.33	−0.47
DLA2 – Deep learning tools are used for predictive maintenance and anomaly detection	.760	3.46	1.09	−0.28	−0.49
DLA3 – Deep learning-based forecasts guide demand, energy and inventory planning	.818	3.47	1.01	−0.33	−0.37
DLA4 – We have the technical expertise and infrastructure (GPU/cloud) to build and deploy deep learning models	.785	3.41	1.00	−0.22	−0.41
Sustainable and Digital HRM Practices (HRM)					
HRM1 – HR policies support flexible work arrangements and work–life balance	.838	3.93	0.91	−0.51	−0.34
HRM2 – Employees receive regular training to work with digital and AI-based systems	.849	3.83	0.99	−0.52	−0.23
HRM3 – Performance appraisal and rewards recognise employee contribution fairly	.797	3.78	0.93	−0.33	−0.46
HRM4 – HR analytics are used to monitor employee workload, engagement and health	.801	3.57	1.06	−0.37	−0.38
Financial Analytics Capability (FIN)					
FIN1 – Financial analytics dashboards provide real-time visibility of costs and cash flows	.795	3.72	0.99	−0.50	−0.35
FIN2 – Predictive financial models are used for budgeting and investment appraisal	.828	3.76	0.99	−0.46	−0.44
FIN3 – Cost–benefit analytics are used to evaluate technology and sustainability investments	.830	3.64	1.02	−0.43	−0.32
FIN4 – Financial and operational data are integrated for managerial decision-making	.756	3.54	1.09	−0.44	−0.40
Environmental Sustainability Performance (ESP)					

Construct and items	FL	M	SD	S	K
ESP1 – Energy consumption per unit of output has reduced over the last three years	.824	3.73	0.97	−0.37	−0.49
ESP2 – Emissions and effluents have decreased over the last three years	.843	3.59	1.01	−0.33	−0.40
ESP3 – Waste generation has reduced and recycling/reuse has increased	.753	3.48	1.04	−0.14	−0.64
ESP4 – Compliance with environmental regulations and standards has improved	.769	3.67	0.96	−0.26	−0.62
Employee Well-Being (EWB)					
EWB1 – Employees in my organisation are satisfied with their jobs and work environment	.816	3.71	0.99	−0.43	−0.23
EWB2 – Employee workload is manageable and does not cause excessive stress	.816	3.72	1.02	−0.49	−0.37
EWB3 – Employees are able to balance their work and personal lives	.838	3.55	1.02	−0.28	−0.43
EWB4 – Employees feel physically and mentally healthy at work	.778	3.73	1.00	−0.47	−0.28
Organizational Performance (OPF)					
OPF1 – Our profitability has improved relative to our major competitors	.814	3.87	0.94	−0.33	−0.87
OPF2 – Employee productivity has increased over the last three years	.760	3.73	1.02	−0.38	−0.69
OPF3 – Operational efficiency (cost, quality and delivery) has improved	.836	3.80	0.99	−0.44	−0.52
OPF4 – Customer satisfaction and market share have improved	.782	3.69	0.99	−0.41	−0.25

Note: FL = EFA factor loading (varimax-rotated); M = mean; SD = standard deviation; S = skewness; K = kurtosis.

5.3. Exploratory factor analysis

We first checked the structure of the 28 items with an EFA, using principal component extraction with Varimax rotation, retaining components with eigenvalues above 1 and suppressing loadings below 0.40. The data were well suited to factoring: the Kaiser-Meyer-Olkin measure was 0.886, which Kaiser (1974) would call meritorious, and Bartlett's test of sphericity was significant (χ^2 (378) = 5653.03, $p < 0.001$).

The analysis produced seven components with eigenvalues above 1, one for each hypothesised construct. Every item loaded on the component it was written for, with loadings between .753 and .849, and the largest cross-loading was only .312. Together the seven components accounted for 73.04% of the variance, comfortably above the 60% level usually expected in social science research (Hair et al., 2019). Table 3 shows that the explained variance was spread fairly evenly, ranging from 10.66% for organizational performance to 10.14% for deep learning analytics capability.

Table 3. Total variance explained and reliability of components.

Component	Items	Eigenvalue	% Variance	Cumulative %	α
Organizational Performance (OPF)	4	2.98	10.66	10.66	0.881
IoT Adoption (IOT)	4	2.97	10.59	21.25	0.867
Sustainable and Digital HRM Practices (HRM)	4	2.96	10.59	31.84	0.876
Environmental Sustainability Performance (ESP)	4	2.91	10.40	42.24	0.873
Financial Analytics Capability (FIN)	4	2.89	10.33	52.58	0.866
Employee Well-Being (EWB)	4	2.89	10.33	62.90	0.865
Deep Learning Analytics Capability (DLA)	4	2.84	10.14	73.04	0.860

Note: Eigenvalues are rotation sums of squared loadings; α = Cronbach's alpha. KMO = 0.886; Bartlett's χ^2 (378) = 5653.03, $p < 0.001$.

5.4. Missing values, outliers, normality and common method bias

The main SEM assumptions were checked before the measurement and structural models were estimated (Kline, 2016). Questionnaires with missing answers had already been removed during screening, so no values were missing. To look for multivariate outliers we used the Mahalanobis distance (D^2) at $p < 0.001$. The largest value, $D^2 = 50.99$, stayed below the critical χ^2 (28) of 56.89, so no case was flagged.

Skewness ranged from −0.61 to −0.13 and kurtosis from −0.87 to −0.09, inside the usual limits of ±2.0 and ±7.0 (West et al., 1995; Curran et al., 1996). Mardia's (1970) multivariate kurtosis was 840.01, against 840.00 expected under multivariate normality (critical ratio = 0.00), so the data showed no meaningful departure from normality. Maximum likelihood estimation was therefore appropriate, and the indirect effects were tested by bootstrapping, which makes no normality assumption about their sampling distribution (Byrne, 2016).

All measures were self-reported and came from one source, so common method bias had to be considered (Podsakoff et al., 2003). On the procedural side, respondents were promised anonymity and told there were no right or wrong answers, items from different constructs were placed apart in the questionnaire, and each firm was represented by managers from several functions. On the statistical side, Harman's single-factor test found that the first unrotated factor explained just 27.98% of the variance, well short of the 50% threshold. Common method bias does not appear to be a serious problem.

5.5. Multicollinearity

To check for multicollinearity among the four capabilities, we looked at their correlations and at collinearity diagnostics. The strongest correlation, between deep learning analytics and financial analytics, was $r = 0.393$, far below Kline's (2016) ceiling of 0.85. Variance inflation factors lay between 1.139 (HRM) and 1.303 (DLA), well under the conservative cut-off of 5 (Hair et al., 2019), and tolerance values (0.768–0.878) were all above 0.10. The four capabilities are therefore distinct enough that collinearity should not distort the structural estimates.

5.6. Confirmatory factor analysis

A first-order CFA of the seven constructs was then run in AMOS 24. Each construct had four indicators and no indicator was allowed to load on more than one construct, giving a congeneric, over-identified model (Hair et al., 2019). Standardised loadings ran from .735 to .854, all significant at $p < 0.001$ and all above 0.70 (Table 4). Fit was good: χ^2 (329) = 491.53, $p < 0.001$,

CMIN/DF = 1.494, RMSEA = 0.037 (90% CI: 0.030–0.044), SRMR = 0.041, CFI = 0.970, TLI = 0.966 and IFI = 0.970 (Hu & Bentler, 1999; Browne & Cudeck, 1993; Bentler, 1990). As is usual with samples of this size, the chi-square test was significant (Byrne, 2016), but the normed chi-square stayed below 3.

5.7. Validity and reliability of the measurement model

Reliability was assessed with Cronbach's alpha and composite reliability. Table 4 shows alpha values from 0.860 (DLA) to 0.881 (OPF) and CR values from 0.861 (DLA) to 0.882 (OPF), all higher than the 0.70 benchmark (Nunnally & Bernstein, 1994; Hair et al., 2019). Convergent validity also held: every standardised loading was significant and above 0.70, and each construct's AVE exceeded 0.50, from 0.608 for DLA up to 0.652 for OPF.

Table 4. Standardised loadings, reliability and convergent validity.

Construct	Items	Standardised loadings	α	CR	AVE	MSV
IOT	IOT1 / IOT2 / IOT3 / IOT4	.799 / .772 / .808 / .769	0.867	0.867	0.620	0.236
DLA	DLA1 / DLA2 / DLA3 / DLA4	.753 / .796 / .813 / .755	0.860	0.861	0.608	0.204
HRM	HRM1 / HRM2 / HRM3 / HRM4	.802 / .839 / .787 / .780	0.876	0.878	0.643	0.166
FIN	FIN1 / FIN2 / FIN3 / FIN4	.778 / .849 / .791 / .736	0.866	0.868	0.623	0.203
ESP	ESP1 / ESP2 / ESP3 / ESP4	.799 / .854 / .797 / .735	0.873	0.874	0.636	0.236
EWB	EWB1 / EWB2 / EWB3 / EWB4	.762 / .843 / .769 / .760	0.865	0.865	0.615	0.208
OPF	OPF1 / OPF2 / OPF3 / OPF4	.813 / .817 / .848 / .749	0.881	0.882	0.652	0.208

Note: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; MSV = maximum shared variance. All loadings significant at $p < 0.001$.

We checked discriminant validity in four ways. The EFA had already shown no meaningful cross-loadings. The highest correlation between any two constructs (IOT–ESP = 0.486) was well under the 0.85 limit (Kline, 2016). Following Fornell and Larcker (1981), the square root of each construct's AVE (Table 5, diagonal) was larger than that construct's correlations with the others, and every MSV was smaller than the corresponding AVE (Table 4). Finally, no HTMT ratio reached the conservative 0.85 cut-off (Henseler et al., 2015); the largest was 0.484 for IOT–ESP (Table 6). The constructs are therefore distinct, and the measurement model can safely be carried forward to the structural analysis.

Table 5. Discriminant validity (Fornell–Larcker criterion): inter-construct correlations with square root of AVE on the diagonal.

Construct	IOT	DLA	HRM	FIN	ESP	EWB	OPF
IOT	0.787						
DLA	0.435	0.780					

Construct	IOT	DLA	HRM	FIN	ESP	EWB	OPF
HRM	0.302	0.181	0.802				
FIN	0.326	0.451	0.338	0.789			
ESP	0.486	0.451	0.245	0.376	0.797		
EWB	0.020	0.054	0.407	0.113	0.117	0.784	
OPF	0.320	0.403	0.303	0.400	0.436	0.456	0.808

Note: Diagonal values in bold are the square roots of AVE; off-diagonal values are latent construct correlations.

Table 6. Heterotrait–monotrait ratio (HTMT).

Construct	IOT	DLA	HRM	FIN	ESP	EWB	OPF
IOT							
DLA	0.437						
HRM	0.309	0.185					
FIN	0.330	0.453	0.337				
ESP	0.484	0.465	0.240	0.387			
EWB	0.030	0.054	0.407	0.115	0.124		
OPF	0.320	0.400	0.305	0.403	0.438	0.459	

Note: All values are below the 0.85 threshold (Henseler et al., 2015).

5.8. Structural model and hypothesis testing

With the measurement model in place, we tested the hypotheses through SEM using maximum likelihood. Two nested models were compared. In Model 1 the four capabilities could reach organizational performance (OPF) only through environmental sustainability performance (ESP) and employee well-being (EWB), that is, full mediation. Model 2 added direct paths from each capability to OPF, so that direct, indirect and total effects could be separated. Both models fitted acceptably (Table 7), but Model 2 fitted significantly better according to the chi-square difference test ($\Delta\chi^2$ (4) = 31.90, $p < 0.001$). We therefore dropped Model 1 and kept Model 2 as the final model (Figure 2).

Table 7. Fit indices of the measurement and structural models.

Index	Measurement model (CFA)	Model 1 (full mediation)	Model 2 (final)	Acceptable range	Source
χ^2 (df)	491.53 (329)	528.17 (336)	496.27 (332)	$p > 0.05$	Byrne (2016)
CMIN/DF	1.494	1.572	1.495	< 3	Wheaton et al. (1977)
RMSEA	0.037	0.040	0.037	< 0.08	Browne & Cudeck (1993)
SRMR	0.041	0.054	0.042	< 0.08	Hu & Bentler (1999)
CFI	0.970	0.965	0.970	> 0.90	Bentler (1990)

Index	Measurement model (CFA)	Model 1 (full mediation)	Model 2 (final)	Acceptable range	Source
TLI	0.966	0.960	0.966	> 0.90	Hu & Bentler (1999)
IFI	0.970	0.965	0.970	> 0.90	Hu & Bentler (1999)
PNFI	0.797	0.808	0.804	> 0.50	Mulaik et al. (1989)
$\Delta\chi^2$ (Δdf)	—	—	31.90 (4), $p < 0.001$	Significant	Byrne (2016)

Note: RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual; CFI = comparative fit index; TLI = Tucker–Lewis index; IFI = incremental fit index; PNFI = parsimony normed fit index. $\Delta\chi^2$ compares Model 1 with Model 2. The chi-square statistic was significant for all models, which is common in samples of this size.

Table 8 sets out the path estimates for the final model. IoT adoption had the largest effect on environmental sustainability performance ($\beta = 0.32$, C.R. = 4.952, $p < 0.001$), which supports H1. Deep learning analytics capability also improved environmental performance ($\beta = 0.24$, C.R. = 3.558, $p < 0.001$), so H2 is supported. HRM practices had a positive but non-significant effect on environmental performance ($\beta = 0.06$, C.R. = 1.055, $p = 0.292$), and H3 is rejected. Financial analytics capability had a smaller yet significant effect ($\beta = 0.15$, C.R. = 2.291, $p = 0.022$), in support of H4. HRM practices had a strong positive effect on employee well-being ($\beta = 0.41$, C.R. = 6.538, $p < 0.001$), supporting H5. Deep learning analytics capability, by contrast, made no significant difference to well-being ($\beta = -0.02$, C.R. = −0.412, $p = 0.680$), so H6 is rejected. On the outcome side, both environmental sustainability performance ($\beta = 0.21$, C.R. = 3.412, $p < 0.001$) and employee well-being ($\beta = 0.41$, C.R. = 6.978, $p < 0.001$) raised organizational performance, supporting H7 and H8.

Two of the four direct paths to organizational performance were significant: financial analytics capability ($\beta = 0.18$, C.R. = 2.945, $p = 0.003$) and deep learning analytics capability ($\beta = 0.18$, C.R. = 2.786, $p = 0.005$). IoT adoption ($\beta = 0.08$) and HRM practices ($\beta = -0.03$) had no significant direct effect. The four capabilities explained 33% of the variance in environmental sustainability performance ($R^2 = 0.33$) and 16% of the variance in employee well-being ($R^2 = 0.16$). The complete model accounted for 44% of the variance in organizational performance ($R^2 = 0.44$).

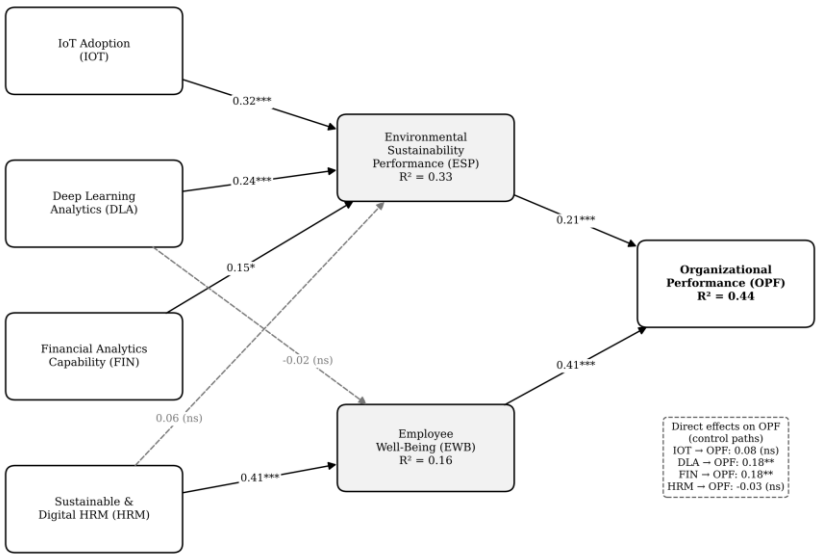


Figure 2. Structural model with standardised path estimates. Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant; dashed grey arrows denote non-significant paths.

Table 8. Summary of results of the direct relationships among constructs.

Hypothesis	Path	β	B	S.E.	C.R.	p	Remark
H1	ESP ← IOT	0.32	0.308	0.062	4.952	***	Supported
H2	ESP ← DLA	0.24	0.239	0.067	3.558	***	Supported
H3	ESP ← HRM	0.06	0.064	0.060	1.055	0.292	Not supported
H4	ESP ← FIN	0.15	0.145	0.063	2.291	0.022	Supported
H5	EWB ← HRM	0.41	0.422	0.065	6.538	***	Supported
H6	EWB ← DLA	−0.02	−0.024	0.057	−0.412	0.680	Not supported
H7	OPF ← ESP	0.21	0.210	0.062	3.412	***	Supported
H8	OPF ← EWB	0.41	0.420	0.060	6.978	***	Supported
—	OPF ← IOT	0.08	0.074	0.059	1.252	0.211	Not significant
—	OPF ← DLA	0.18	0.177	0.064	2.786	0.005	Significant
—	OPF ← HRM	−0.03	−0.035	0.062	−0.562	0.574	Not significant
—	OPF ← FIN	0.18	0.175	0.060	2.945	0.003	Significant

Note: β = standardised estimate; B = unstandardised estimate; S.E. = standard error; C.R. = critical ratio. ***$p < 0.001$. R^2 (ESP) = 0.33; R^2 (EWB) = 0.16; R^2 (OPF) = 0.44.

5.9. Direct, indirect and total effects

To test whether environmental sustainability performance and employee well-being carry the effects of the capabilities, we used bias-corrected bootstrapping with 2,000 resamples and 95% confidence intervals (Preacher & Hayes, 2008). An indirect effect counts as significant when its interval excludes zero. We classified the results following Zhao et al. (2010). A significant indirect effect without a significant direct effect is indirect-only, or full, mediation. Significant indirect and direct effects with the same sign amount to complementary, or partial, mediation. A significant direct effect paired with a non-significant indirect effect is direct-only, meaning no mediation.

Table 9 shows that IoT adoption affected organizational performance through environmental sustainability performance (β = 0.067, 95% CI [0.032, 0.121]), while its direct effect was not significant. This is full mediation, and H9a is supported. Deep learning analytics capability worked both through environmental sustainability (β = 0.050, 95% CI [0.020, 0.107]) and directly (β = 0.177), a case of complementary partial mediation that supports H9b. Financial analytics capability followed the same pattern, with a significant indirect effect (β = 0.031, 95% CI [0.006, 0.070]) alongside a significant direct effect (β = 0.178), so H9d is supported. HRM practices, however, did not work through environmental sustainability (β = 0.013, 95% CI [−0.012, 0.048]), and H9c is rejected.

The effect of HRM practices on organizational performance ran entirely through employee well-being. This indirect effect was the largest in the model (β = 0.169, 95% CI [0.100, 0.244]), and the direct effect was not significant (β = −0.033), so H10a is supported. Deep learning analytics capability did not act through well-being (β = −0.010, 95% CI [−0.061, 0.040]); along this route its effect on performance was direct only, and H10b is rejected. Looking at total effects, deep learning analytics (β = 0.217) and financial analytics (β = 0.209) had the greatest overall influence on organizational performance, followed by HRM practices (β = 0.149) and IoT adoption (β = 0.144). All four total effects were significant.

Table 9. Direct, indirect and total effects on organizational performance (bootstrapping, 2,000 resamples).

Hyp.	Path	Direct effect	Indirect effect	95% BC CI (indirect)	Total effect	Mediation type	Remark
H9a	IOT → ESP → OPF	0.077 (0.269)	0.067 (***)	[0.032, 0.121]	0.144 (0.025)	Full (indirect-only)	Supported
H9b	DLA → ESP → OPF	0.177 (0.008)	0.050 (***)	[0.020, 0.107]	0.217 (***)	Partial (complementary)	Supported
H9c	HRM → ESP → OPF	−0.033 (0.607)	0.013 (0.333)	[−0.012, 0.048]	0.149 (0.006)	No mediation (no effect)	Not supported
H9d	FIN → ESP → OPF	0.178 (0.004)	0.031 (0.015)	[0.006, 0.070]	0.209 (***)	Partial (complementary)	Supported
H10a	HRM → EWB → OPF	−0.033 (0.607)	0.169 (***)	[0.100, 0.244]	0.149 (0.006)	Full (indirect-only)	Supported
H10b	DLA → EWB → OPF	0.177 (0.008)	−0.010 (0.654)	[−0.061, 0.040]	0.217 (***)	No mediation (direct-only)	Not supported

Note: Standardised estimates with bootstrap p-values in parentheses; BC CI = bias-corrected confidence interval. ***p < 0.001. Total effect is the total effect of the capability on OPF across all modelled pathways.

5.10. Multi-group analysis: manufacturing versus service firms

H11 was tested by estimating Model 2 separately for manufacturing (n = 196) and service (n = 164) firms. Both groups fitted acceptably (manufacturing: CMIN/DF = 1.297, RMSEA = 0.039, SRMR = 0.050, CFI = 0.968; services: CMIN/DF = 1.352, RMSEA = 0.046, SRMR = 0.058, CFI = 0.954), so the configural model held in each sector. We then compared paths with critical ratios for differences, treating $|z| > 1.96$ as significant at the 5% level (Byrne, 2016).

The results are in Table 10. HRM practices did far more for employee well-being in service firms ($\beta = 0.61$) than in manufacturing firms ($\beta = 0.21$; $z = -3.422$, $p < 0.001$). In manufacturing, IoT adoption ($\beta = 0.38$ vs 0.27) and deep learning analytics ($\beta = 0.30$ vs 0.16) had somewhat larger effects on environmental sustainability, and well-being had a larger effect on performance ($\beta = 0.49$ vs 0.30), but none of these gaps was statistically significant. H11 is thus partly supported. The model is largely the same in both sectors, and the HRM–well-being path is where they clearly differ.

Table 10. Multi-group comparison of structural paths (manufacturing vs services).

Hyp.	Path	Manufacturing β (p)	Services β (p)	z (difference)	p	Remark
H1	ESP ← IOT	0.38 (***)	0.27 (0.004)	1.042	0.298	No difference
H2	ESP ← DLA	0.30 (0.002)	0.16 (0.075)	1.375	0.169	No difference
H3	ESP ← HRM	0.02 (0.822)	0.10 (0.265)	−0.708	0.479	No difference
H4	ESP ← FIN	0.12 (0.159)	0.15 (0.125)	−0.120	0.905	No difference
H5	EWB ← HRM	0.21 (0.011)	0.61 (***)	−3.422	***	Significant difference

Hyp.	Path	Manufacturing β (p)	Services β (p)	z (difference)	p	Remark
H6	EWB ← DLA	0.04 (0.664)	−0.08 (0.295)	1.018	0.309	No difference
H7	OPF ← ESP	0.17 (0.057)	0.26 (0.004)	−0.883	0.377	No difference
H8	OPF ← EWB	0.49 (***)	0.30 (0.003)	1.498	0.134	No difference

Note: z = critical ratio for the difference between unstandardised coefficients. ***p < 0.001.

6. DISCUSSION

We begin with the model's explanatory power. The four capabilities explained 33% of the variance in environmental sustainability performance, and the whole model explained 44% of the variance in organizational performance. Only 16% of the variance in employee well-being was explained, which is not surprising: well-being also depends on job design, leadership and people's personal lives, none of which the model includes (Bakker & Demerouti, 2007; Guest, 2017). Overall, technological, human and financial capabilities together account for a substantial part of organisational outcomes, though each works through its own channel.

IoT adoption was the strongest driver of environmental sustainability performance, and its whole effect on organizational performance passed through environmental results. IoT, it seems, does not create value on its own. It does so by making resource flows visible and controllable, which brings down energy intensity, emissions and waste, much as Industry 4.0 studies (Kamble et al., 2018; Ghobakhloo, 2020) and the NRBV (Hart, 1995) would predict. The weakest IoT item was the use of alerts to trigger corrective action. Many firms appear to be gathering sensor data without closing the loop between what they monitor and what they do about it, and that gap is an obvious place to improve environmental performance.

Deep learning analytics capability reached organizational performance by two routes, one through environmental results and one direct. The direct route probably reflects better forecasting, maintenance and planning, which make operations more efficient and customers more satisfied whether or not the environment benefits; similar effects have been reported for big data analytics capability (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019). The environmental route is consistent with earlier findings that predictive analytics helps environmental sustainability (Dubey et al., 2019; Bag et al., 2020). Deep learning capability also had the lowest mean score, which suggests that the firms in this region have much of its potential still to realise.

Deep learning analytics capability had no effect on employee well-being, and this result deserves attention. Whatever relief intelligent systems give by taking over routine work may be cancelled out by the demands they bring: new tools to learn, closer monitoring and a faster pace, all documented in the technostress literature (Tarafdar et al., 2007). Seen through the JD-R model, a technology is not automatically a resource or a demand. What it becomes depends on how it is introduced and on the people practices that surround it (Bakker & Demerouti, 2007).

HRM practices were the main source of employee well-being, and well-being had the largest effect of any variable on organizational performance, so the HRM–well-being–performance chain produced the biggest indirect effect in the model. This fits the JD-R model well, as well as the view that well-being is a key link between HRM and performance (Van De Voorde et al., 2012; Guest, 2017; Wright & Cropanzano, 2000). HRM practices did not, however, improve environmental sustainability performance in any significant way. Our HRM measure centred on work–life support, digital training, fair appraisal and HR analytics for workload, not on green goals. People-oriented HRM apparently does not spill over into environmental results by itself; as green HRM scholars argue, environmental objectives have to be written into HRM systems on purpose (Renwick et al., 2013; Jabbour & de Sousa Jabbour, 2016; Ren et al., 2018).

Financial analytics capability helped environmental sustainability and also had its own direct effect on organizational performance. The environmental effect suggests that once a firm can measure costs and returns precisely, it finds it easier to justify and rank sustainability projects. The direct effect points to tighter cost control, budgeting and investment appraisal (Chen

et al., 2012; Davenport & Harris, 2007). With one of the largest total effects in the model, financial intelligence deserves more attention than it usually gets in discussions of digital transformation for sustainability.

The multi-group results show that the model holds in broadly the same form for manufacturing and service firms, with one clear exception: HRM practices did much more for well-being in services. In service work, where knowledge and customer contact dominate, flexibility, development and fair recognition are probably the job resources employees value most. In manufacturing, physical working conditions and shift patterns may limit how far HRM policies can reach. Technology had larger effects on environmental outcomes in manufacturing, as one would expect from its bigger physical footprint, but the difference was not statistically significant.

6.1. Theoretical implications

The study contributes to theory in several ways. It brings IoT, deep learning, HRM and financial analytics into one structural model and shows that they are empirically separate capabilities, which takes the RBV and dynamic capabilities perspectives beyond studies of a single technology. Treating environmental sustainability and employee well-being as parallel mediators shows that technological capabilities create value mainly by an environmental route and HRM mainly by a human route, which is in keeping with the NRBV and the JD-R model respectively. The absence of any effect of deep learning on well-being, or of HRM on environmental performance, warns against assuming that digital or people capabilities help across the board; each works on particular outcomes. The study also introduces financial analytics capability as a separate antecedent of environmental and organizational performance. Finally, the sector comparison adds evidence from an emerging economy and shows that the HRM–well-being link depends on context.

6.2. Managerial implications

For managers, industry bodies and policy makers, several practical lessons follow. IoT adoption had the strongest link with environmental performance, so firms should extend sensor monitoring beyond energy to water, emissions and waste, connect IoT data to their enterprise systems and, most of all, put procedures and clear responsibility in place for acting on IoT alerts. Investment in deep learning should concentrate on the areas where firms are weakest, namely skills and computing infrastructure, and on uses such as predictive maintenance and energy optimisation that improve both environmental and operational results.

Deep learning does not improve well-being by default, so any rollout should come with change management, training, a review of workloads and limits on intrusive monitoring. HR departments should keep building flexible work, digital training, fair appraisal and HR analytics on workload and health, because these practices produce the largest indirect gains in performance, particularly in services. If firms want HRM to help the environment too, they need to put environmental goals into training, appraisal and rewards explicitly. Finance teams should build analytics that put a value on sustainability projects and link financial with operational data. At the regional level, the governments of Andhra Pradesh and Telangana and the industry associations in these clusters could help smaller suppliers through shared IoT and analytics facilities, skills programmes and incentives tied to measured environmental gains.

7. CONCLUSION

If firms are to perform sustainably, they need to know how their digital, human and financial capabilities shape results for the environment, for employees and for the business. We built and tested an integrated model with data from 360 managers in 64 manufacturing and service firms in Andhra Pradesh and Telangana, using covariance-based SEM. The EFA identified seven distinct constructs, and the CFA confirmed the reliability, convergent validity and discriminant validity of the measurement model, with good fit. Checks on normality, outliers, multicollinearity and common method bias gave no cause for concern.

IoT adoption, deep learning analytics and financial analytics all improved environmental sustainability performance, IoT most of all, while HRM practices did not. HRM practices were the main source of employee well-being, and deep learning analytics made no difference to it. Environmental sustainability performance and employee well-being both raised organizational performance. IoT's effect on performance worked entirely through environmental sustainability, deep learning and financial analytics worked partly through it, and HRM's effect worked entirely through well-being. The link between HRM and well-being was much stronger in service firms than in manufacturing. Technology and people capabilities, then, improve

organizational performance by different but complementary routes. Firms will get the full value of their investment only if they run IoT, deep learning, HRM and financial analytics as one system that serves both the environment and their employees.

7.1. Limitations and future research

The study has its limitations. The data are cross-sectional and come from 360 managers in 64 firms in two states, chosen by purposive-cum-stratified sampling, so causal claims are limited and the results may not apply to other regions or to small enterprises. Longitudinal designs with larger probability samples would help here. Although several functions were represented in each firm, all measures were perceptual and self-reported; future studies could add objective data such as energy intensity, emissions records and financial ratios. Our analysis was at the respondent level, and multilevel models that aggregate to the firm would separate within-firm from between-firm effects. The model could also be extended with constructs such as green HRM, technostress, digital leadership, top management commitment and environmental regulation, and could test interactions between technological and human capabilities. Comparisons across more industries, firm sizes and countries would show how far the findings travel.

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